UNIVERSITY OF BELGRADE
SCHOOL OF ELECTRICAL ENGINEERING

Sofija S. Spasojević

QUANTITATIVE MOVEMENT ANALYSIS IN THE REHABILITATION OF NEUROLOGICAL DISORDERS USING VISION AND WEARABLE SENSORS

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Sofija S. Spasojević

KVANTITATIVNA ANALIZA POKRETA U REHABILITACIJI NEUROLOŠKIH POREMEĆAJA KORIŠĆENJEM VIZUELNIH I NOSIVIH SENZORA

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COMMISSION FOR THESIS EXAMINATION AND EVALUATION

Supervisor: dr Željko Đurović, Full profesor,
University of Belgrade, School of Electrical Engineering

Supervisor: dr José Alberto Rosado dos Santos-Victor, Full professor,
University of Lisbon, Instituto Superior Técnico

dr Branko Kovačević, Full professor,
University of Belgrade, School of Electrical Engineering

dr Aleksandar Rodić, Research Fellow,
University of Belgrade, Mihailo Pupin Institute

dr Jorge Marques, Full professor,
University of Lisbon, Instituto Superior Técnico

dr Luís Alexandre, Full professor,
University Beira Interior

Defense date:

Abstract

Neurological disorders, such as Parkinson's disease (PD) and stroke, lead to serious motor disabilities, decrease the patients' quality of life and can cause the mortality. Early diagnosis and adequate disease treatment are thus crucial factors towards keeping the disease under control in order to enable the normal every-day life of patients. The treatment of neurological disorders usually includes the rehabilitation therapy and drug treatment, that are adapted based on the evaluation of the patient state over time. Conventional evaluation techniques for diagnosis and monitoring in neurological disorders rely on the clinical assessment tools i.e. specially designed clinical tests and scales. However, although beneficial and commonly used, those scales are descriptive (qualitative), primarily intended to be carried out by a trained neurologist, and are prone to subjective rating and imprecise interpretation of patient's performance.

On the other side, the traditional rehabilitation sessions in a hospital environment are often a slow, tedious, disempowering and non-motivational process. In severe conditions, the assistance of the other people is mandatory, which increases the time consumptions and overall costs.

In this thesis, new sensing/processing techniques are proposed intended to support the traditional clinical practice. We design a reliable, portable and affordable system, suitable for home rehabilitation, which combines vision-based and wearable sensors. Next, we develop an objective approach for quantitative evaluation of the movement performance. The special emphasis is on the design of quantitative Movement Performance Indicators (MPIs) that are extracted from the collected sensor data. A set of rehabilitation movements is defined, with the supervision of neurologists and therapists for the specific case of Parkinson's disease and stroke. It comprises full-body movements measured with a Kinect device, fine hand movements, acquired with a data glove and arm/hand movements collected using the armband Electromyography (EMG) device.

Our first focus is the quantitative evaluation of the full-body movements (gait and upper body movements) of Parkinson's patients. We develop the approach for quantitative movement assessment and propose two groups of MPIs: (i) MPIs well-known in medical practice that are usually assessed by obsolete (imprecise) techniques and (ii) newly-proposed MPIs, suggested by the doctors, that cannot be calculated using conventional techniques. Next, we investigate whether the clinical groups of interest

(patients vs. controls and disease stages) can be identified based on the proposed MPIs. In the frame of the developed approach for quantitative movement assessment, we propose the method for therapeutic exercise segmentation based on a predictive Gaussian model and event detection principle.

Second, we concentrate on the quantification of the fine hand movements of Parkinson's patients using the data glove. The hand movement behavior is very important for PD assessment since the main symptoms, such as rigidity and tremor, are primarily spotted during the hand movement performance. Again, we propose new MPIs to characterize the hand motion, that can be used by doctors to support their decisions during diagnosis and monitoring evaluations. Additionally, we investigate whether the proposed MPIs are correlated with official clinical scales in Parkinson's disease for their possible inclusion into the medical protocols.

Furthermore, in the third part of the thesis, we examine the arm/hand movements of Parkinson's patients relying on the EMG and Inertial measurement unit (IMU) data from an armband device. Our goal is to reveal whether the low-cost armband sensor can be a suitable alternative for the expensive data glove. In addition, we want to address the important aspects that were not covered by previous analysis: (i) inspection of bradykinesia motor symptom and (ii) assessment of the performance differences between left and right arm/hand movements.

Finally, in the last part of the thesis, our goal is to support the progress monitoring of the stroke patients using the sensor data. The approach to the quantification of the movement performance in the post-stroke period is patient-oriented and focused only on the progress monitoring. We design the application for storing, visualization and interpretation of the patients' data to support the post-stroke clinical evaluations by medical doctors. The personal patient profiles are built based on the collected clinical and sensor data.

Developed approaches for movement quantification are validated based on the experiments with Parkinson's disease and stroke patients, conducted in the clinical environment.

Keywords: Parkinson's disease, stroke, vision and wearable sensors, wireless sensors, gait, upper body movements, arm/hand movements, movement quantification, Movement Performance Indicators

Scientific field: Electrical and Computer Engineering

Scientific subfield: Signal processing and machine learning

Sažetak

Neurološka oboljenja, kao što su Parkinsonova bolest i šlog, dovode do ozbiljnih motornih poremećaja, smanjuju kvalitet života pacijenata i mogu da uzrokuju smrt. Rana dijagnoza i adekvatno lečenje su krucijalni faktori za držanje bolesti pod kontrolom, kako bi se omogućio normalan svakodnevni život pacijenata. Lečenje neuroloških bolesti obično uključuje rehabilitacionu terapiju i terapiju lekovima, koje se prilagođavaju u skladu sa stanjem pacijenta tokom vremena. Tradicionalne tehnike evaluacije u dijagnozi i monitoringu neuroloških bolesti oslanjaju se na kliničke evaluacione alate, tačnije specijalno dizajnirane kliničke testove i skale. Međutim, iako su korisne i najčešće korišćene, kliničke skale su sklone subjektivnim ocenama i nepreciznoj interpretaciji performanse pacijenta.

Sa druge strane, tradicionalna rehabilitaciona terapija u bolničkim uslovima je često spor, monoton i obeshrabrujući proces. U ozbiljnim stanjima, asistencija drugih ljudi je neophodna, što zahteva dodatno vreme i povećava ukupne troškove.

U ovoj tezi, predložene su nove senzorske tehnike i tehnike obrade senzorskih signala, namenjene za podršku tradicionalnoj kliničkoj praksi. Dizajnirali smo pouzdan, prenosiv i jeftin sistem, pogodan za kućnu rehabilitaciju, koji kombinuje senzore zasnovane na viziji i nosive senzore. Razvili smo objektivan pristup za kvantitativnu analizu performanse pokreta. Poseban naglasak je na dizajnu kvantitativnih Indikatora Performanse Pokreta (IPP-a) koji su izdvojeni iz prikupljenih podataka sa senzora. Set rehabilitacionih pokreta je definisan u dogovoru sa neurolozima i terapeutima posebno za Parkinsonovu bolest i šlog. Set se sastoji od hoda i pokreta gornjeg dela tela, izmerenih pomoću Kinekt-a, finih pokreta ruku, snimnjenih sa senzorskom rukavicom i pokreta ruke/šake prikupljenih pomoću EMG senzora u vidu narukvice.

Naš prvi fokus je na kvantitativnoj evaluaciji hoda i pokreta gornjeg dela tela za Parkinsonove pacijente. Razvili smo pristup za kvantitativnu evaluaciju pokreta i predložili dve grupe IPP-a: (i) IPP-ovi koji su dobro poznati u medicinskoj praksi, ali se do njih dolazi zastarelim i nepreciznim tehnikama i (ii) novo-predloženi IPP-ovi, sugerisani od strane doktora, koji ne mogu biti izmereni tradicionalnim tehnikama. Nakon toga istražujemo da li kliničke grupe od interesa (pacijenti i kontrolna grupa, kao i različiti stadijumi bolesti) mogu biti identifikovani na osnovu predloženih IPP-ova. U okviru razvijenog pristupa za kvantitativnu evaluaciju pokreta, predlažemo metod za

segmentaciju rehabilitacionih vežbi, zasnovanu na prediktivnom Gausovom modelu i principu detekcije događaja.
U drugoj fazi, koncentrišemo se na kvantifikaciju finih pokreta šake Parkinsonovih pacijenata pomoću senzorske rukavice. Analiza pokreta šake je od velikog interesa kod Parkinsonove bolesti, obzirom da se glavni simptomi, kao što su rigidnost i tremor, inicijalno primećuju u pokretima šake. Slično kao u prvom delu, predlažemo nove IPP-ove za karakterizaciju pokreta šake, koji mogu biti korišćeni od strane doktora za podršku kliničkih evaluacija tokom dijagnostike i monitoringa bolesti. Takođe, istražujemo da li su predloženi IPP-ovi korelisani sa zvaničnim kliničkim skalama u Parkinsonovoj bolesti, kako bi se ispitala mogućnost njihovog uključivanja u medicinske protokole.
U nastavku, u trećem delu teze, bavimo se pokretima ruke/šake kod Parkinsonovih pacijenata oslanjajući se na EMG i IMU (Inertial Measurement Unit) podatke dobijene pomoću EMG senzora u vidu narukvice. Naš cilj je da otkrijemo da li jeftin narukvica-senzor može biti adekvatna zamena za veoma skupu senzorsku rukavicu korišćenu u prethodnom delu. Dodatno, bavimo se važnim aspektima koji nisu analizirani do sada: (i) ispitivanje simptoma bradikinezije (usporenost pokreta) i (ii) procena razlike u performansi između pokreta leve i desne ruke/šake.
Konačno, u poslednjem delu teze, naš cilj je da podržimo monitoring pacijenata nakon šloga korišćenjem podataka sa senzora. Pristup za kvantifikaciju performanse pokreta u periodu nakon šloga je usmeren na pojedinačne pacijente i glavni fokus je na monitoringu bolesti. Dizajnirali smo aplikaciju za skladištenje, vizualizaciju i interpretaciju senzorskih podataka za podršku kliničkih evaluacija u periodu nakon šloga. Lični profili pacijenata su napravljeni na osnovu prikupljenih kliničkih i senzorskih podataka.
Razvijeni pristupi za kvantifikaciju pokreta su validirani na osnovu eksperimenata sa pacijentima koji imaju Parkinsonovu bolest ili se oporavljaju nakon šloga. Svi eksperimenti su sporovedeni u kliničkim uslovima.

Ključne reči: Parkinsonova bolest, šlog, senzori zasnovani na viziji, nosivi i bežični senzori, hod, pokreti gornjeg dela tela, pokreti ruke/šake, kvantifikacija pokreta, Indikatori Performanse Pokreta

Naučna oblast: Elektrotehnika i računarstvo

Uža naučna oblast: Obrada signala i mašinsko učenje

Resumo

As disfunções neurológicas, tais como a doença de Parkinson e acidente vascular cerebral (AVC), originam incapacidades motoras graves, diminuem a qualidade de vida dos pacientes e podem causar a morte. Um diagnóstico precoce e o tratamento adequado da doença são, portanto, factores cruciais para manter a doença sob controlo, a fim de permitir uma vida quotidiana normal aos pacientes. O tratamento destas disfunções neurológicas geralmente inclui reabilitação e medicação, que são adaptados ao longo do tempo com base na avaliação do estado do paciente. As técnicas de avaliação convencionais para diagnóstico e monitorização de disfunções neurológicas apoiam-se em ferramentas de avaliação clínica, ou seja, testes e escalas clínicas desenvolvidas especialmente para o efeito.

Por outro lado, as sessões de reabilitação tradicionais em ambiente hospitalar são muitas vezes um processo lento, tedioso e não motivacional. Em condições mais severas, é obrigatória a assistência de outras pessoas, o que aumenta o tempo e por sua vez os custos globais.

Nesta tese, são propostas novas técnicas de detecção/processamento destinadas a apoiar a prática clínica tradicional. É apresentado um sistema confiável, portátil e acessível, adequado a reabilitação domiciliar, e que combina sensores baseados na visão e wearables. Em seguida, é desenvolvida uma abordagem objectiva para uma avaliação quantitativa do desempenho dos movimentos. É dada uma ênfase especial na concepção de Indicadores quantitativos de Desempenho de Movimento (Movement Performance Indicators – MPIs) que são extraídos dos dados recolhidos dos diversos sensores. Um conjunto de movimentos de reabilitação é definido, com a supervisão de neurologistas e terapeutas para o caso específico da doença de Parkinson e AVC. Estes incluem movimentos de corpo inteiro medidos com um dispositivo Kinect, movimentos finos das mãos adquiridos com uma data glove e movimentos de braço/mão recolhidos usando uma braçadeira de Electromiografia (EMG).

O nosso primeiro foco é a avaliação quantitativa de movimentos de todo o corpo (marcha e movimentos do tronco) de pacientes de Parkinson. Desenvolvemos uma abordagem para a avaliação quantitativa de movimento e propomos dois grupos de Indicadores de Desempenho de Movimento (MPIs): (i) MPIs bem conhecidos da prática médica que são habitualmente medidos com recurso a técnicas obsoletas (imprecisas)

e (ii) novos MPIs propostos, sugeridos por doutores, que não podem ser calculados através de técnicas convencionais. Posteriormente, investigamos se os grupos clínicos de interesse (pacientes vs. controlo, e diferentes estados da doença) poderiam ser identificados através dos MPIs propostos. Enquadrando-se no desenvolvimento da abordagem para a avaliação quantitativa de movimento, propomos um método para segmentação de exercícios terapêuticos baseado em modelos Gaussianos preditivos e no principio de deteção de eventos.
Segundo foco, concentramo-nos na quantificação dos movimentos finos da mão em pacientes de Parkinson usando a data glove. O comportamento dos movimentos da mão na avaliação da doença de Parkinson é muito importante dado que os principais sintomas, como rigidez e tremores, são inicialmente observados durante a realização de movimentos manuais. De novo, propomos novos MPIs caracterizadores de movimentos manuais que podem ser usados por doutores no suporte das suas decisões durante o diagnostico e avaliações de monotorização. Adicionalmente, investigamos se os MPIs propostos estão correlacionados com as escalas clínicas oficiais da doença de Parkinson para a sua possível inclusão nos protocolos médicos.
Ademais, na terceira parte da tese, examinámos o movimento do braço/mão de pacientes de Parkinson dependendo dos dados EMG e IMU fornecidos pela braçadeira wireless Myo. O objetivo sendo o de revelar se o sensor de baixo custo poderá ser uma alternativa apropriada à custosa data glove. Adicionalmente, queremos abordar os aspetos importantes deixados de fora da analise anterior: (i) inspeção do sintoma motor bradicinesia e (ii) avaliação das diferenças de desempenho entre movimentos do braço/mão esquerdo e direito.
Por fim, na última parte da tese, o nosso objetivo é o de auxiliar a monotorização de progresso em pacientes de acidente vascular cerebral (AVC) através do uso dos dados de sensores. A abordagem à quantificação do desempenho do movimento no período pós-AVC é orientada ao paciente e focado apenas na monotorização do progresso. Nós projetamos a aplicação para armazenamento, visualização e interpretação dos dados do paciente para auxílio das avaliações clínicas pós-AVC por doutores médicos. Os perfis pessoais dos pacientes são construídos com base nos dados clínicos e dados recolhidos pelos sensores.
As abordagens desenvolvidas para a quantificação de movimento são validadas com base em experiências com pacientes de Parkinson e AVC, realizadas em ambiente clínico.

Palavras chave: Doença de Parkinson, Acidente Vascular Cerebral, sensores de visão e wearable, sensores sem fios, marcha, movimentos do tronco, movimentos do braço/mão, quantificação de movimento, Indicadores de Desempenho de Movimento

To my parents Vera and Slobodan,
and to my sisters Smilja and Senka

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List of Acronyms

MPI Movement Performance Indicator

HY Hoehn and Yahr

UPDRS Unified Parkinson's Disease Rating Scale

PD Parkinson's disease

MOCAP Marker-based motion capture

SAA Shoulder abduction-adduction

SFE Shoulder flexion-extension

HBM Hand boundary movement

ROM Range of Motion

SR Symmetry Ratio

FFEM Fingers flexion and extension movement

FECM Fingers expansion and contraction movement

FTM Finger-tapping movement

ROHM Rotation of the hand movement

DH Denavit-Hartenberg

RH-EE Rotation of the hand movement with elbow extended

RH-EF Rotation of the hand movement with elbow flexed at 90°

GPP-EL Movement of object grasping, pick and place in the case of easy load

GPP-HL Movement of object grasping, pick and place in the case of heavy load

TT-P Proximal tapping task

TT-D Distal tapping task

L

EMG Electromyography

IMU Inertial measurement unit

BWLP Butterworth low-pass filter

ICC Intraclass correlation coefficient

CI 95% confidence interval

LDA Linear Discriminant Analysis

LASSO Least Absolute Selection Shrinkage Operator

AV Angular velocity

ACC Acceleration

SVM Support vector machines

KNN K-nearest neighbors

RBF Radial basis function

MLP Multilayer perceptron

ACC Accelerometer

GYRO Gyroscope

MAV Mean absolute value

VAR Variance

WC Waveform change

SSI Simple square integral

RAN Range

EMG-MAV Mean absolute value from EMG signal

EMG-VAR Variance from EMG signal

EMG-WC Waveform change from EMG signal

ACC-SSI Simple square integral from accelerometer signal derivative

ACC-RAN Range from accelerometer signal derivative

GYRO-SSI Simple square integral from gyroscope signal derivative

GYRO-RAN Range from gyroscope signal derivative

ROC Receiver operating characteristic curve

AUC Area under the curve

NIHSS The National Institutes of Health Stroke Scale

BI Barthel index

upperbody1 Hand goes from the ear to the hip (same body side)

upperbody2 Hand goes from the ear to the hip (different body side - diagonal)

upperbody3 Shoulder flexion-extension

upperbody4 Shoulder abduction-adduction

upperbody5 Elbow flexed at 90°: hands go up and down in the shoulder joint

VSED Vertical shoulder-elbow distance

VDBH Vertical distance between hands

MSA Mean shoulder angle

MS Movement speed

arm/hand1 Elbow flexed at 90°: Palm goes up and down

arm/hand2 Arm stretched: Palm goes up and down

arm/hand3 Elbow flexed at 90°: pronation and supination

arm/hand4 Arm stretched: pronation and supination

arm/hand5 Movement of object grasping, pick and place: easy load

arm/hand6 Movement of object grasping, pick and place: heavy load

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Chapter 1

Introduction

1.1 Motivation

Neurological disorders, such as Parkinson's disease [Jankovic, 2008] and stroke, cause impaired motor control and reduced movement performance. Depending on the disease stage, patients can experience difficulties during the gait, large range movements, and fine hand movements. Consequently, the every-day activities become limited and the quality of life decreases. Traditional rehabilitation sessions in a hospital environment are often a slow, tedious, disempowering and non-motivational process. In severe conditions, the assistance of the other people is mandatory, which increases the time consumptions and overall costs.

On the other side, conventional evaluation techniques in neurological disorders rely on the clinical assessment tools i.e. specially designed clinical tests and scales. Clinical scales are descriptive and offer limited possibilities for assessment of the patient condition. The widely used clinical scales for Parkinson's disease (PD) assessment are Hoehn and Yahr (HY) [Goetz et al., 2004] and Unified Parkinson's Disease Rating Scale (UPDRS) [Goetz et al., 2008]. According to the HY scale, patients can be assigned into one of the five levels. The consequence of such distribution can be a placement of the patients with significantly different condition into the same group. UPDRS scale has more levels and decisions are made based on the evaluation of different aspects such as gait, upper body and hand movements, balance, posture and stability, even the facial expressions and speech. Even if the UPDRS scale is more informative than HY scale, decisions are still prone to subjective evaluations, which can lead to the imprecise interpretation of the patient's state.

The most popular clinical scale for evaluations in stroke is the Fugl-Meyer scale [Fugl-Meyer et al., 1974]. Patients are scored using the three-level rating system (0-2). Their performance across five aspects of clinical interest is taken into account: motor function, sensory function, balance, joint range of motion and joint pain. For each category, corresponding movements are defined by the protocol. The final outcome is

summarized to one particular value resulting from all tests.

Poor patient motivation and necessity for other persons' support are critical factors that can be overcome with a sensor system, designed for home rehabilitation. Additionally, there is a clear need for introducing new sensing/processing techniques into the clinical practice, capable to enhance the evaluation procedures in neurological disorders.

Over the past years, progress in data-analysis and sensing technologies [Stamford et al., 2015] opened new possibilities for improving conventional rehabilitation practice. However, introducing novel technologies into medical protocols is still challenging, mainly due to: (i) high equipment cost; (ii) system complexity and reliability; (iii) need for a technical support during therapy sessions; (iv) lack of correlation between clinical and technical performance indicators and (v) lengthy and arduous process to obtain the clinical licenses.

Different types of sensor devices are used nowadays for the movement acquisition. Rough division addresses three main groups of the sensor devices suitable for the movement data collection: (i) vision-based with markers, (ii) vision-based without markers and (iii) wearable sensors. The vision-based systems with markers (Marker-based motion capture (MOCAP) systems) [Zhou and Hu, 2008] involve the placement of the markers at particular body points and complex system of cameras for movement recording. Those systems deliver accurate measurements, but they are extremely costly and complex for use. In addition, MOCAP systems are not portable and the recordings need to be carried out in the specially designed environments. On the other side, low-cost marker-free MOCAP systems such as the Kinect and Xtion [Gonzalez-Jorge et al., 2013; Goncalves et al., 2015; Anton et al., 2015] become very popular as a suitable alternative for expensive, complex and non-portable MOCAP systems. Using these new-generation devices, the movements can be acquired without markers, based on the inbuilt algorithms for skeleton tracking. The performance of lower-cost systems has been tested and shown to possess a satisfactory accuracy for the application in the rehabilitation therapy [Khoshelham and Elberink, 2012; Clark et al., 2012; Chang et al., 2012]. However, their performance is quite lower in comparison to the advanced MOCAP systems and the readings are less robust to measurement noise. Still, they represent a good trade-off between the overall performance and cost.

Wearable sensors are attached to the body parts and the data are collected during the movement performance. The connection between the wearable sensors and PC for storing the data can be wired or wireless. The wired connection restricts the movements and limits the data acquisition to the particular place. On the other side, wireless wearable sensors are more flexible in terms of portability and available workspace. There are two main groups of the wearable sensors: (i) isolated sensors such as accelerometers [Yokoe et al., 2009; Stamatakis et al., 2013] and gyroscopes [Dai et al., 2015; Djurić-Jovičić et al., 2017] and (ii) a number of sensors integrated into one de-

vice. The device might contain the same type sensors, such as data gloves ([Iacono et al., 1995; Su et al., 2001, 2003; Morrow and Burdea, 2006; Niazmand et al., 2011; Cyb]). On the other side, some wearable sensor devices incorporate different types of sensors ([Myo]).

Rehabilitation studies for neurological disorders usually focus on the analysis of particular body functionalities, such as postural control [Galna et al., 2014b], gait [Lange et al., 2012; Cho et al., 2009], upper body movements [Lum et al., 2002] or even the observation of a specific joint [Vaisman et al., 2013].

Under this thesis, the aim is to develop a reliable, portable and affordable system, suitable for home rehabilitation, which combines vision-based and wearable sensors. The system is intended to support the conventional rehabilitation therapy (both during diagnosis and progress monitoring asessment). It is designed for the objective evaluation of the movement performance in the context of all movements relevant for the clinical protocols. We address the gait, large range upper body movements, arm/hand and fine hand movements. The special emphasis is on the design of quantitative movement indicators, extracted from the collected the sensor data. A novel approach for examining and characterizing the rehabilitation movements, using quantitative descriptors is proposed.

A set of experimental exercises is defined with the supervision of neurologists and therapists for the specific case of Parkinson's disease (PD) and stroke. Full-body movements (gait and large range upper body movements) are measured with a Kinect device, fine hand movements are acquired with a data glove and the arm/hand movements are collected with a EMG armband sensor (Figure). After acquired sensor data, the next challenge consists in defining suitable features that can be used to characterize the movements in the different subject conditions. Such features are denoted as MPIs for assisting both diagnosis and monitoring. The proposed MPIs are built upon domain-specific knowledge and provided by doctors and therapists as well as data analysis. Particular MPIs have not been used in the movement evaluations so far, but turn out to be informative for clinical aspects in neurological disorders.

The main objectives of this PhD thesis are following:

- Developing a portable, reliable and affordable sensor system, suitable for home rehabilitation, which combines vision-based and wearable sensors.
- Introducing a novel approach for examining and characterizing the rehabilitation movements, using quantitative descriptors MPIs.
- Design of the new MPIs that are extracted from sensor data and quantify the movements of different body/arm/hand parts, and that can be used by therapists for diagnosis and progress assessment.

1.2 Medical background

1.2.1 Parkinson's disease

Parkinson's disease PD was originally described two centuries ago by the London physician and naturalist James Parkinson. Today, it still remains a challenge burdened with numerous dilemmas to both clinicians and researchers around the world. PD is the second most common neurodegenerative disease (after Alzheimer's type dementia) and according to the traditional understanding, it is related to the extinction of the specific neuronal populations (dopaminergic neurons). This process primarily occurs in the nuclei of the brain stem (mesencephalon), and it comes with the aging process. However, in the case of Parkinson's disease, this type of decay of nerve cells assumes a very rapid progression and leads to serious consequences. There are two main disease types, according to the traditional division: (i) idiopathic (or typical) Parkinson's disease (75% of cases), and Parkinsonism (Parkinson's syndrome). The first entity refers to the typical clinical presentation, non-hereditary disease with a favorable response to dopaminergic compositions. The autopsy reveals six stages of neuronal loss, astrocytic gliosis, and the formation of typical inclusions in different brain regions [Braak et al., 2002]. Epidemiological studies reveal that the number of PD patients in the United States today is around 1 million and every 10 minutes the new patient is diagnosed with PD, which is about 60.000 new patients per year [Olanow and Koller, 1998]. However, along with the "aging" of the population and the extension of life expectancy, projections for the future really seem alarming. If the present trend continues, about 2040. year, neurodegenerative diseases (PD, motor neuron disease and dementia) will overcome the malignant diseases and will take the second place among the most common causes of death in the elderly population [Lilienfeld and Perl, 1993]. Prior to the widespread use of a levodopa preparation, it was considered that PD substantially shortens the lifetime of a patient. The epidemiological studies at that time reported that the average survival rate after the diagnosis was about 9-10 years [Hoehn and Yahr, 1967]. The introduction of levodopa therapy has significantly changed this trend, primarily in the sense of improved symptomatic disease control and prevention of immobility, falls, serious disorders and other life-threatening complications [Rajput, 2001]. However, the long-term usage of this therapy has contributed to the manifestation of motor complications and behavioral disorders, which independently affect the mortality of patients. Still, the disease significantly shortens the lifetime of a patient [Morens et al., 1996]. The origin and the nature of the disease are still not finally revealed, although two hypotheses are dominate – a genetic theory and the theory of the contribution of the environmental factors. Previous opinions represented PD as a typical non-hereditary disease. However, along with the strong expansion of new molecular genetic techniques in the early 1990s and with the discovery of several large families with well-defined patterns of inheritance, this opinion was undermined. The

association of the inheritance patterns of dominant or recessive type is verified for eight genetically defined loci [Vila and Przedborski, 2004]. Still, the majority of PD cases (sporadic form) do not show any family aggregation and possible genetic factors. Consequently, the genetic factors only increase the risk, but do not automatically predict the disease. An alternative hypothesis on the environmental factors considers a number of factors ranging from selective or combined exposure of metals (manganese, copper, lead, iron), pesticides (insecticides, herbicides, fungicides), or engaging in agricultural industry (growing of certain crops or animals) as well as possible risk factors for the development of the disease in susceptible individuals. A series of the epidemiological studies have revealed a protective role of smoking and drinking caffeine [Morens et al., 1995]. Such unusual findings arouse controversy to the issue of whether the inverse correlation between these factors and disease development are only the artifacts of inadequate study design. However, in the following studies, the findings about the protective role of smoking and drinking caffeine in the context of PD are confirmed [Morens et al., 1995; Costa et al., 2001]. The diagnosis of PD is established based on the neuropathological review [Hughes et al., 1992]. The recognition of the three main clinical symptoms is necessary – tremor, rigidity and akinesia (involuntary movements). The fourth symptom can be the disorder of balance and postural control. However, the frequency of non-recognition of the disease is relatively high (up to 24% of newly diagnosed cases during systematic testing of the elderly) [de Rijk et al., 1997], but on the other hand, necropsy findings show that the diagnosis is often established with no grounds, also in about 24% [Rajput et al., 1991]. Consequently, a strong emphasis is placed on the application of the UK Parkinson's Disease Society Brain Bank clinical diagnostic criteria. This criteria in addition to the aforementioned 4 cardinal symptoms, takes into account 16 criteria of the diagnosis exclusion and an additional 8 criteria to support the disease progression and response to levodopa, [Hughes et al., 1992]. In response to this tendency, more recent reports of monitoring the reliability of the diagnosis are corrected by providing an accuracy of about 90%, even though limited to specialized institutions for treating PD [Hughes et al., 2002]. In addition to these clinical criteria, there are numerous attempts of introducing the more exact tests for diagnosis establishment. Between neurophysiological procedures, only a few earned particular attention. The most common are differential diagnostic markers with a certain discriminant values, such as the sympathetic skin response, heart rate variability and pathological electromyography findings, but without high specificity tests necessary for the application in practice [Tolosa et al., 2006]. On the other side, olfactory function tests have proven to be highly sensitive as an early sign of the PD, found in about 90% of the patients [Katzenschlager and Lees, 2004]. Magnetic resonance of the brain rarely provides a contribution to the diagnosis. With the exception of atrophy patterns of specific brain regions in rare syndromes similar to PD [Lang et al., 1994], the overall sensitivity of this approach does not exceed 60-80% [Bhattacharya et al.,

2002]. With regard to the treatment of PD, substantial changes occur from year to year related to the introduction of new pharmacological compositions and the development of a number of substances having a potentially curative effect. The principles of the disease treatment are defined depending on the disease stage, whether it is the case of an early or advanced stage. Symptomatic therapy in patients in the early stage of the disease is delayed until the moment when the functional requirements dictate the need for introducing the therapy. The therapy approach is still individualized, primarily depending on the age of the respondents; in younger patients, levodopa products are introduced as late as possible. This principle has been established based on the observations of long-term complications associated with levodopa application in the fields of the motor and behavioral disorders [Olanow et al., 2001]. Before that time, the patient is referred to pharmacological agents with neuroprotective potential. However, there is no category of medications declared beyond doubt to stops or slows down the natural flow of the disease. In terms of the available surgical procedures intended for the treatment of PD, the modern medicine mostly relies on the ablative procedures, procedures of neuro-stimulations (deep brain stimulation) and augmentative or restorative procedures of the direct application of therapeutic agents by surgery. Among all techniques, the deep brain stimulation is a very common and the most explored method, which is approved for the widespread use by the US Food and Drug Administration in 2002. The application of the high-frequency stimulation leads to the inhibition of excessive activated sub-thalamic core, one of the key relay of neural circuits of the basal ganglia. This procedure reduces its effect on the output projection of the basal ganglia and normalizes the activation of premotor cortex, which is clinically related to Parkinsonian symptoms [Volkmann, 2007]. In addition to the pharmacological and surgical treatment principles, the role of the rehabilitation in the treatment of people with PD becomes more and more popular in recent years. These efforts are mostly focused on the improving of walking, balance, coordination, strength and functionality of the patients. The general consensus on the role of the rehabilitation techniques says that exercises help. However, there is no uniform or generally accepted protocol for the rehabilitation of these patients. Stretching exercises, exercises with the resistance, various forms of balance training and aerobic exercises are commonly applied [Salgado et al., 2013]. On the other side, the movement protocol is established as a part of clinical scales (HY [Goetz et al., 2004] and UPDRS [Goetz et al., 2008]), intended to evaluate the patients' state and monitor their disease progress. The evaluation of the patients' movement performance is based on the visual inspection by doctors, hence prone to subjective and imprecise ratings. Recently, various sensor devices are used for movement acquisition in medical protocols. New sensing and data processing techniques opened the possibility for objective evaluation of the movement performance. Based on the sensor data, the relevant movement performance indicators can be designed and used as a support to clinical evaluations. Consequently, it is expected that

the application of the sensor technologies and computer science will be the next step towards more precise diagnosis and progress monitoring evaluations in PD.

1.2.2 Stroke

Stroke is a leading cause of motor disability, the second most common cause of death in general [Lozano et al., 2013], and the third, taking into account the countries of the developed world [Cheeran et al., 2009]. Approximately 80% of individuals that survive stroke suffer the neurological damage that leads to impairments of the motor functions and, consequently, long-term disability and limited every-day activities [Langhorne et al., 2009]. Ischemic stroke represents the 80% of the all stroke cases [Thrift et al., 2001]. It represents sudden, focal brain injury, which is the result of the arterial occlusive or bleeding in the brain [Warlow et al., 2011]. Ischemic stroke occurrence leads to the progressive death of neurons due to the interruption of the blood flow. Opposite to the ischemic stroke, the hemorrhagic form is usually caused by the braking of the small extensions formed in the brain blood vessels [Auer and Sutherland, 2005]. This process can be a consequence of the high-pressure disease. Some types of the hemorrhagic stroke are based on the bleeding due to the braking of the large blood vessels in the brain, when the blood effuses into the brain parenchyma. Those events are related to the individual congenital malformations or the weakness of the blood vessel wall (arterial-venous malformations), or even less frequently acquired conditions, dangerous for the artery integrity [Thrift et al., 2001]. The modern diagnostic algorithm requires the urgent differentiation of the two mentioned stroke forms, taking into account the substantially different principles of the treatment. The gold standard for the diagnosis establishment are neuro radiological methods of visualization of the brain parenchyma and blood vessels of the brain - computerized tomography (CT) and nuclear magnetic resonance (NMR). Occlusion of the blood vessel leads to the ischemic brain lesion, whose central part is a necrosis zone, i.e. zone of the brain tissue with damaged neurons, which is irretrievably lost. However, this zone is surrounded by the reversible ischemia zone, so-called ischemic penumbra and in this zone, the structural damage of neurons is not definitive. Still, there exists the functional damage because of the reduction in the blood flow [Fisher, 2004]. Consequently, if the blood flow does not back to normal, the damage of the neurons is permanent. Hence, there are two opposite types of dying neurons. The necrosis is the main mechanism of the neurons damage taking place in the core of ischemia. On the other side, the apoptosis is the predominant mechanism of the neuronal damage in the penumbra, where a milder degree of the ischemia is present [Fisher, 2004]. Therefore, the aim of the therapeutic intervention is to preserve the penumbra, since the rescue of this tissue is directly related to the neurological improvement and recovery [Donnan et al., 2007].
In most cases, stroke causes the damaged function of the one arm/hand. Consequently,

in the post-stroke period, clinicians use different techniques for the arm/hand recovery. The most common therapy approaches are following: (i) neurodevelopmental techniques, whereby the most widespread is the Bobath technique [Bobath, 1990]; (ii) repeated training focused on the particular task [French et al., 2007]; (iii) treatment based on the limited usage of the healthy arm [Taub et al., 1993]; (iv) sensory stimulation [Smania et al., 2003]; (v) multi-sensory rehabilitation techniques [Shams and Seitz, 2008]; (vi) mirror therapy [Garry et al., 2005] and (vii) training in the virtual environment and robotics [Holden, 2005; Broeren et al., 2008]. The choice of the rehabilitation therapy depends on the patient condition and damage severity.
The most common clinical scales for evaluation of the therapeutic intervention effect are the following: (i) Jebsen-Taylor scale - modified test of the hand motor skills, [Jebsen et al., 1969] and (ii) Fugl-Meyer scale - addresses various aspects of clinical interest such as motor function, sensory function, balance, joint range of motion and joint pain. It evaluates force, reflex and arm coordination in the range [0-100], whereby 66 points belongs to the hand motion and 34 points relate to the leg motion. It represents the most used clinical scale for evaluations in stroke, [Fugl-Meyer et al., 1974]. However, both clinical scales are prone to subjective and imprecise ratings, as it was the case for Parkinson's disease. Consequently, new sensing/processing technologies would open the possibility for objective evaluations during the patients' recovery from stroke.

1.3 Thesis outline

The remaining of the document is structured as follows. Chapters 3, 4 and 5 introduce the approaches for quantitative assessment of the full-body (Chapter 3), hand (Chapter 4) and arm/hand (Chapter 5) movements in Parkinson's disease. For quantification of the full-body movements we use Kinect device, the hand movements we acquired with the sensor glove data, while the arm/hand movements are collected using Electromyography (EMG) armband device. The general structure of these chapters is the same, whereby some sections are topic-particular. At the beginning of each chapter, the focused background research is presented. Then, the proposed system structure is introduced, followed by experimental procedure. The core of the chapters is the extraction of the quantitative measurements, which we call Movement Performance Indicator (MPI), from the sensor signals. In the following, the comprehensive analysis of the proposed MPIs is conducted according to the general and clinical aspects of interest: (i) internal consistency of the sensor measurements and reliability of MPIs; (ii) establishment of the new feature space in the procedure of dimensionality reduction and determining the most relevant MPIs using feature selection methods; (iii) discrimination (classification) between the patients and controls, and between the disease stages based on the designed MPIs (support to disease diagnosis and progress monitoring, respectively); (vi) correlation of the proposed MPIs with clinical scales. Finally,

we give an overview of an approach and conclude the chapters. Chapter 6 presents an approach for quantitative assessment of the full-body and arm/hand movements of patients recovering from the stroke. The structure of the first part of this chapter is the same as in previous chapters in the sense of the following sections: background research, proposed system structure, experimental procedure, Movement Performance Indicator (MPI) extraction. However, for the stroke patients, the focus is not on distinguishing between the groups of interest (patients vs controls and disease stages), as it was the case in Parkinson's disease. Instead, the main emphasis is on the progress monitoring aspect. Consequently, we design the MPIs in order to support the progress monitoring of the patients in the post-stroke period. We develop the application with personal profile for each patient that gives insight into the movement performance over time. Additionaly, we assess the diferences between hand affected by the stroke and the healthy hand in the context of Movement Performance Indicator (MPI) and clinical scales.

Chapter 2

Background and Related Work

Over the past years, the progress in data-analysis and sensing technologies [Stamford et al., 2015] opened new possibilities for the movement performance assessment in rehabilitation practice of neurological disorders. Rough division addresses three main groups of the sensor devices suitable for the movement data collection: (i) vision-based with markers, (ii) vision-based without markers and (iii) wearable sensors. The vision-based systems with markers (Marker-based motion capture (MOCAP) systems) [Zhou and Hu, 2008] are often used for movement acquisition during rehabilitation sessions, because of their ability to deliver accurate measurements, in spite of their extremely high costs. Other alternatives include the attachment of different sensors to the patient's body [Parisi et al., 2015; Patel et al., 2012] or hand (data glove) and, more recently, low-cost marker-free MOCAP systems such as the Kinect and Xtion [Gonzalez-Jorge et al., 2013; Goncalves et al., 2015; Anton et al., 2015]. The performance of lower-cost systems has been tested and shown to possess a satisfactory accuracy for the application in the rehabilitation therapy [Khoshelham and Elberink, 2012; Clark et al., 2012; Chang et al., 2012]. While some examples of Kinect-based rehabilitation systems are described in [Chang et al., 2013, 2011; Gama et al., 2012; Calin et al., 2011], little attention has been devoted to the specific case of PD [Galna et al., 2014a,b].

In [Chang et al., 2011] the authors develop Kinerehab – rehabilitation system for helping people with motor disabilities. The system is based on the skeleton tracking and joint positions obtained from Kinect. Collected data are analyzed in order to check if the rehabilitation movement standard is achieved. The system is tested on students with three different exercises. However, the authors have not explained the algorithm for movement assessment and verification and they have not discussed the accuracy of measurements. In addition, the larger number of tested exercises and experiments with patients would be necessary for final verification of the approach. The similar idea is presented in [Gama et al., 2012] where the authors develop the system for guidance and movement correction, based on the Kinect data. They analyze the

Shoulder abduction-adduction (SAA) movement and take into account the Range of Motion (ROM) of shoulder and elbow angle, as well as the relative position between particular joints of interest. However, they focus only on one rehabilitation movement, which results in a limited movement performance evaluation. Recently, authors in [Galna et al., 2014a] have studied the Kinect accuracy for measuring movements of Parkinson's patients, but they did not implement automatic movement analysis. They compared the Kinect to the VICON MOCAP system through a set of rehabilitation exercises. Their results suggest similar temporal accuracy between the two systems when measuring the movement duration and spatial accuracy regarding the upper body movements. Their general conclusion is that the Kinect has the potential to be used for movement analysis in PD and a promising application in the future for home rehabilitation. To raise the patient's motivation during therapy, some studies have introduced virtual environments into data acquisition and processing procedures for PD [Galna et al., 2014b; Albiol-Perez et al., 2012]. The outcome of studies [Galna et al., 2014a,b] are questionnaires about patients' experience after using the specially designed games for rehabilitation. The signal processing procedure behind the game interface is not presented. The main limitations with the use of virtual environments and rehabilitation games are the lack of official safety-evidence and proof of clinical effectiveness. The overall conclusion is that many Kinect-based studies related to the movement quantification for rehabilitation purposes lack the description about actual movement indicators extracted from the Kinect sensor data. In this thesis, we explain in detail the approach for movement quantification and in addition to the standard measurements of movement speed and range of motion, we propose the novel MPIs to characterize upper body movements in PD - Symmetry Ratio (SR) and the measure of tremor.

An important aspect when dealing with the sensor signals is the pre-processing step, due to its high influence on the further analysis and results. In our experiments with Kinect, the data for several consecutive movements are collected inside one signal sequence, but they are analyzed separately. Consequently, we pay particular attention to the segmentation procedure. We propose a novel segmentation algorithm based on the predictive event approach in order to verify the results of the segmentation approach based on the local maxima and minima.

In general, segmentation procedure is very present in gesture recognition tasks, since it can have a huge impact on the classification rate of the gesture recognition system. Gesture segmentation and recognition systems have significant applications in many different fields such as virtual and augmented reality, industrial process control, physical rehabilitation, human-robot interaction, computer games etc. Frequently used methods for gesture segmentation are based on the Dynamic Programming (DP) [Alon et al., 2005; Oka, 1998], Dynamic Time Warping (DTW) [Darrell et al., 1996] and Hidden Markov Models (HMM) [Chen et al., 2003; Wilson and Bobick, 1999]. A

technique based on the simple sliding window combined with simple moving average filter is used in [Kwon, 2008]. The author defines the content of each gesture in the following form: starting static posture, dynamic gesture part and ending static posture. In addition, to obtain a more robust segmentation, the author observes also the length of each analyzed sequence to eliminate the appearance of the static part into dynamic part of the gesture. In [Kahol et al., 2004] the authors developed an algorithm for segmentation of dance sequences. This algorithm, called Hierarchical Activity Segmentation, is based on the division of the human body onto hierarchically dependent structures. They take into account relevant motion parameters for body segments (segmental force, kinetic energy and momentum) that characterize motion in the levels of defined hierarchy. In [Kocian et al., 2005] the authors took a dynamical system approach for dynamic system identification, however, that approach did not account for sensor noise. A prediction-based approach to event segmentation, relying on an adaptive dynamical system approach was presented in [Nery and Ventura, 2011, 2013]. Here, we consider a different approach employing a probabilistic model (Gaussian processes) as a machine learning method [Rasmussen and Williams, 2006] that provides information about both, value and uncertainty. This method has shown good properties related to complexity model, processing time and remarkable results in comparison with commonly used method of the first derivative.

In recent years, various types of wearable sensors have been developed and proposed for measuring and evaluating hand movements: gyroscopes [Dai et al., 2015; Djurić-Jovičić et al., 2017], accelerometers [Yokoe et al., 2009; Stamatakis et al., 2013], magnetic sensors [Kandori et al., 2004; Shima et al., 2008, 2009] and force sensors [Niazmand et al., 2011; Prochazka et al., 1997]. These sensor systems can only modestly contribute to the hand movement assessment. Specifically, the use of one or two isolated sensors in motion acquisition limits the movement quantification, due to the limited amount of the collected data. In [Djurić-Jovičić et al., 2017] the authors propose the approach for quantitative finger-tapping assessment based on the 3D gyroscopes placed on the thumb and index-finger. They design one quantitative indicator called tapping angle and calculate its value across eleven different tapping patterns. The setup procedure is not time-consuming, as well as the post-processing of the collected sensor data. This makes the proposed approach suitable for the inclusion into clinical protocols. However, the approach itself is not comprehensive enough to support clinical evaluations. The motion of other fingers, as well as additional quantitive indicators, should be considered. The authors in [Stamatakis et al., 2013] use a low-cost triaxial accelerometer-based system placed on the index finger to quantify finger-tapping task in Parkinson's disease. They have extracted movement features such as movement time, frequency, opening angle, root mean square etc. Even promising for the clinical practice in the sense of simplicity and low-cost design, the study lacks the correlation analysis between the proposed features and official clinical scale ratings. Magnetic

sensor with two coils attached on the fingers is used in [Shima et al., 2008, 2009] for measurement and evaluation of finger tapping movements. The proposed features for movement characterization are fingertip distance, velocity, and acceleration. However, the system is prone to orientation errors and sensitive to the nearby presence of metallic objects.

Data gloves address the shortcoming of isolated sensors by integrating multiple sensors in one single, more sophisticated, device. Most data glove-based systems have a wired connection between the glove and the PC for storing data, which can interfere with the patient's motion and degrade their comfort [Iacono et al., 1995; Su et al., 2001, 2003; Morrow and Burdea, 2006]. A wireless system, with five sensors embedded in the data glove (two touch sensors, two 3D-accelerometers and a force sensor) is examined in [Niazmand et al., 2011]. The focus is on the assessment of PD motor symptoms such as bradykinesia, tremor and arm/hand rigidity. However, the study lacks the finger joint motion tracking and correlation with clinical scales. Additionally, the approach is tested based on the data for six PD patients. The larger experimental set is necessary towards final verification of the proposed method.

For the hand movement assessment in this thesis, the wireless Cyber Glove II is used, a device with eighteen sensors that output joint angular data [Cyb]. Although this system is relatively costly, it has been tested as a proof of concept, towards the design of an affordable version of this data glove for application in the rehabilitation practice. In the available literature, there are no studies using the Cyber Glove II for quantification of hand movements in PD assessment [Maetzler et al., 2013].

We propose the comprehensive approach for hand and finger movement analysis across four different therapeutic movements suggested by the neurologist. The extracted hand movement performance indicators relate to the hand wrist and finger joints range of motion (metacarpal and proximal joints), angular velocities obtained from the abduction sensors (placed between each two consecutive fingers) and fingertip velocity and acceleration parameters (derived from the hand model). Consequently, our approach overcomes the limitation of the previous studies that focus on the particular hand points or deliver the insufficient number of quantitative indicators. In addition, we correlate our scores with official clinical ratings and identify the movement performanse indicators that are the most correlated with clinical scales.

Another common approach for arm/hand movement evaluation in neurological disorders is the muscle activity analysis. The standard approach for obtaining the muscle activity information is the placement of the surface Electromyography (EMG) electrodes on the skin, which detect the electrical potential generated by muscles. The main drawback of the standard EMG electrodes is the wired connection with a device for EMG signal representation. Consequently, muscle activity tests are available only in the hospital environment. Investigation of the muscle activity using EMG electrodes information for the particular case of PD is reported in ([Robichaud et al., 2002; De Michele

et al., 2003; Nieuwboer et al., 2004; Meigal et al., 2009]). However, all those studies collect the EMG data using surface electrodes relying on the wired system. The analysis of the muscle activity is also reported in the recent studies concerning PD ([Ruonala et al., 2014; Rissanen et al., 2015; Ghassemi et al., 2016]). The authors in ([Ruonala et al., 2014; Rissanen et al., 2015]) particularly observe the muscles' behaviour during deep brain stimulation. They report that Parkinson's disease symptoms change the EMG signal properties and suggest that EMG analysis is able to detect differences between the deep brain stimulation settings. The authors in ([Ghassemi et al., 2016]) use the EMG data, along with the readings from the accelerometer, to successfully differentiate essential tremor from Parkinson's disease (PD). While the studies ([Ruonala et al., 2014; Rissanen et al., 2015; Ghassemi et al., 2016]) concentrate on the muscle activity of upper limbs, the study ([Nieuwboer et al., 2004]) deals with the EMG analysis of lower limbs in order to detect freezing of the gait episodes.

The authors have suggested many different features to characterize the EMG signals in the time domain ([Phinyomark et al., 2009, 2012; Rissanen et al., 2015; Ghassemi et al., 2016; Huang et al., 2013; Arief et al., 2015; Boostani and Moradi, 2003; Meigal et al., 2009; De Michele et al., 2003]) and frequency domain ([Phinyomark et al., 2009, 2012; Boostani and Moradi, 2003; De Michele et al., 2003]). The two most common approaches for EMG signal analysis are wavelet transform ([De Michele et al., 2003; Ghassemi et al., 2016]) and window approach ([Phinyomark et al., 2009; Boostani and Moradi, 2003]). We have adopted the window approach and the features suggested in the literature that emphasize the amplitude characteristics of EMG signal. Such choice has been convinient for our case and it is explained in detail later in the section.

The wireless Myo armband device incorporates two types of sensor data into one device: the EMG data from eight EMG channels and the Inertial measurement unit (IMU) data (from the accelerometer and gyroscope). The accelerometer and gyroscope have been widely tested in studies related to PD and showed significant potential towards quantification of PD symptoms ([Ghassemi et al., 2016; Bächlin et al., 2010; Kim et al., 2011; Tripoliti et al., 2013]). The authors in ([Bächlin et al., 2010]) use accelerometers, while the authors in ([Tripoliti et al., 2013]) use both, accelerometers and gyroscopes, to observe the gait characteristics in PD patients. They state that freezing of the gait episodes can be detected using sensor data, along with the feedback about gait performance. The study ([Kim et al., 2011]) focuses on the quantification of bradykinesia from finger-tapping movement using two gyroscopes placed on the fingers. Although the results of bradykinesia quantification using gyroscope data are promising, the analysis is limited to one movement and two sensors. The overall conclusion is that signals from accelerometer and gyroscope demonstrate meaningful patterns in the patient's movements and reveal the presence / intensity of the disease motor symptoms. Like in the case of EMG signals, we concentrate on the signal features from accelerometer and gyroscope that take into account the signal amplitude characteristics.

This wireless armband device has been launched very recently and only a few studies report some preliminary results concerning its inclusion into medical protocols ([Sathiyanarayanan and Rajan, 2016; Lipovsky and Ferreira, 2015; Qamar et al., 2015]). However, to the best of our knowledge, it has not been previously used in any study regarding the quantification of the arm/hand movements in PD assessment.

In recent studies, the use of an armband device has been considered for medical and rehabilitation applications, especially for physiotherapy healthcare ([Sathiyanarayanan and Rajan, 2016]) and recovery after the stroke ([Lipovsky and Ferreira, 2015]). The authors in ([Sathiyanarayanan and Rajan, 2016]) use MYO Diagnostics application for medical diagnosis and to understand how comfortable subjects feel while performing the movements using the armband device. The study ([Lipovsky and Ferreira, 2015]) proposes a low-cost rehabilitation system for recovery after the stroke, which consists of an armband device and a data glove. The authors present just the concept of a rehabilitation system based on the virtual environment and gaming to enhance the patient's motivation. Both studies ([Sathiyanarayanan and Rajan, 2016; Lipovsky and Ferreira, 2015]) lack the signal processing, feature extraction analysis, and decision-making mechanisms behind the interface.

In ([Qamar et al., 2015]) the authors propose a multi-sensory gesture-based occupational therapy system, which consists of a Kinect v2, a Leap motion sensor and a Myo armband device. The system is intended to support the everyday activities in the home environment and to encourage the patients to practice and obtain the feedback about their movement performance during usual daily routines. Again, as in ([Sathiyanarayanan and Rajan, 2016; Lipovsky and Ferreira, 2015]) only the concept of the system is presented, along with the general implementation details.

Work under this thesis overcomes the scope of conceptual studies published so far, by introducing the comprehensive processing modules and interpretation of the sensor measurements from armband device. We propose new scores for the arm/hand movement characterization denoted as MPIs, like in the previous chapters. The MPIs are intended to support diagnosis and monitoring evaluations, as well as the assessment of the motor symptoms, with a special emphasis on bradykinesia. The MPIs we propose are built upon both domain-specific knowledge, provided by movement disorder experts, as well as data analysis. They are primarily designed in accordance with clinically relevant aspects and tested towards official clinical tests and scales. We thus propose an upgrade to the affordable, reliable and portable sensor system, proposed in the previous chapters. We develop an approach for movement quantification, with the potential to be used as a support for the conventional motor performance evaluations and possibility of home rehabilitation.

Stroke is a neurodegenerative disorder, which causes impaired motor functions, mostly in the upper limbs. Recovering from stroke includes a lengthy rehabilitation procedure to recover the limb functionality. Evaluation of the patient's success during rehabil-

itation sessions is carried out using clinical scales [Fugl-Meyer et al., 1974] that are prone to subjective rating and imprecise interpretation of patient's performance. The recent development of the affordable sensing technologies can potentially improve and support traditional evaluation techniques. The main benefits of the sensory systems would be relying on the objective approach and the possibility of home rehabilitation. There are a lot of sensor-based systems used in rehabilitation for large-range upper body movement acquisition and later evaluation. Marker-based motion capture (mocap) systems [Zhou and Hu, 2008] are often used for movement acquisition in general. They are well-known as extremely accurate systems, but also extremely costly. Other alternatives include the integration of different sensor types attached to the patient's body [Parisi et al., 2015; Patel et al., 2012] and, more recently, low-cost marker-free mocap systems such as Kinect and Xtion [Gonzalez-Jorge et al., 2013; Goncalves et al., 2015; Anton et al., 2015]. The performance of lower-cost systems has been tested and shown to possess a satisfactory accuracy for the application in the rehabilitation therapy [Khoshelham and Elberink, 2012; Clark et al., 2012; Chang et al., 2012; Fernandez-Baena et al., 2012] and specifically for stroke rehabilitation applications [Webster and Celik, 2014]. While some examples of Kinect-based rehabilitation systems are described in [Chang et al., 2013, 2011; Gama et al., 2012; Calin et al., 2011], little attention has been devoted to the specific case of stroke [Exell et al., 2013; Esfahlani and Thompson, 2016; Bao et al., 2013; Hondori et al., 2012; Zannatha et al., 2013; Sadihov et al., 2013].

Authors in [Exell et al., 2013] use Kinect as a support device during Functional electrical stimulation (FES) in addition to surface electrodes, electro-goniometer and the data glove device. The study focuses on the small range arm/hand movements (reaching tasks). Kinect is intended for the calculation of the shoulder and elbow angle, while the wrist angle is measured with the electro-goniometer and the data glove. The movement performance evaluation is limited only to those joint angles (shoulder, elbow and wrist). The study [Esfahlani and Thompson, 2016] proposes the game-based concept to assist the physiotherapy after stroke. Kinect and Myo armband sensor are intended for tracking the patient's (player's) movements. The study lacks the proof of concept in the sense of the system testing through experiments with patients, as well as the signal processing, feature extraction and movement evaluation procedure behind the game interface. Authors in [Bao et al., 2013] perform the Kinect-based virtual reality training for motor functional recovery of upper limbs after subacute stroke. However, the evaluation after the training is based only on the clinical assessment tools (Fugl-Meyer and the Wolf Motor Function Test) and by observing the changes in activated brain regions (Functional magnetic resonance imaging – fMRI). Their conclusion is that the Kinect-based virtual reality training promotes the recovery of upper limb motor function after subacute stroke, however, the assessment of the patient's state does not include the Kinect data analysis. The authors in [Hondori et al., 2012] evaluate the

food-related tasks as activities of daily living (ADL), intended for post-stroke patients. They use Kinect to measure joint positions and angles of interest and inertial sensors to measure the acceleration. The system was tested only for healthy subjects, hence its further evaluation with the stroke patients is necessary. The authors in [Zannatha et al., 2013]. develop the system based on the 3D vision using Kinect, accompanied by virtual environment, ergonometric signals and a humanoid (Nao) for stroke rehabilitation. The study proposes a large set of potential quantitative measurements, resulting from the kinematics of the upper limbs (joint rotations and distances between the joints), as well as the information based on the electromyography, goniometry, and inertial measurements. Nao robot represents the role of the therapist – to check how well the patients repeat the exercises and to encourage them during rehabilitation sessions. However, the study lacks the experimental verification with patients and evaluation of their performance based on the proposed set of quantitative measurements. The study [Sadihov et al., 2013] introduces the virtual rehabilitation system for stroke patients, composed of the Kinect device and haptic glove for tactile feedback. Kinect is used to track the upper limbs and to map the information to a virtual avatar. The authors provide their system with database and data visualization blocks for the further evaluations, but it is not highlighted in detail in the paper how the sensor data take part in the performance evaluations. The study requires further experiments with patients to confirm the eligibility of the proposed system for (home) rehabilitation applications.

Many different types of wearable sensors are used nowadays for rehabilitation purposes [Patel et al., 2012]. Some common problems of the majority of wearable systems are: (i) wired connection – patients' movements are limited due to the restricted workspace and the system is set to one particular place (e.g. medical center); (ii) limited amount of the collected movement data – some systems are relevant only for the small set of movements and output the insufficient data for the comprehensive movement analysis (e.g. one or two isolated sensors); (iii) high cost; (iv) system complexity and need for a technician support.

New low-cost wireless wearable technologies open the possibility for flexible and extensive data acquisition, bringing the opportunity for home rehabilitation. Particular new-generation devices output various types of sensor data for comprehensive movement analysis. Recently launched Myo armband sensor [Myo] is a promising low-cost wireless wearable device. This device is placed on the forearm and outputs the Electromyography (EMG) data from eight channels. The armband device contains also 3-axis accelerometer and 3-axis gyroscope, which output acceleration and angular velocity information, respectively. Some convenient applications of the Myo armband sensor relate to gesture recognition [Boyali et al., 2015], sign language recognition [Abreu et al., 2016], controlling of the robotic arm (virtual or real) [Shin et al., 2015; Yang et al., 2015] etc. However, a number of recent studies focus on its application for rehabilitation and physiotherapy.

Brain damage resulting from a stroke is often followed by muscle weakness in the limbs. Therefore, the Electromyography (EMG) analysis [Gallina et al., 2016; Suresh et al., 2015] and EMG stimulation [Wilson et al., 2016; Dorsch et al., 2014] are widely used for evaluation of patients' condition and recovery after a stroke. However, the majority of studies use the wired surface EMG electrodes to obtain the muscle activity information. Such approach can restrict patients' movements and limit the application of the approach only to medical centers and hospitals. In addition, as suggested in [Woodford and Price, 2007], the evaluations of patients' condition after stroke cannot rely only on EMG analysis. Similarly, the EMG stimulation should be accompanied with the standard physiotherapy [Wilson et al., 2016; Dorsch et al., 2014; Woodford and Price, 2007]. Our study evaluates the upper body movements based on the Kinect data and arm/hand movements using combined EMG and IMU data from armband device. Thus, the insight into patients' motor performance and their overall condition result from multiple aspects.

The accelerometer and gyroscope data are commonly used to support traditional evaluation techniques in the post-stroke treatments [Noorkõiv et al., 2014; Narai et al., 2016; Mizuike et al., 2009; Laudanski et al., 2015; Chaeibakhsh et al., 2016; Delva and Menon, 2016]. Some studies employ only acceleration information [Noorkõiv et al., 2014; Narai et al., 2016; Mizuike et al., 2009], while others combine both, accelerometer and gyroscope data [Laudanski et al., 2015; Chaeibakhsh et al., 2016; Delva and Menon, 2016]. Sensors are mainly placed on the both wrists [Noorkõiv et al., 2014; Narai et al., 2016; Chaeibakhsh et al., 2016; Delva and Menon, 2016], but also worn on the waist [Narai et al., 2016; Mizuike et al., 2009] or sternum [Chaeibakhsh et al., 2016], attached below the knee [Laudanski et al., 2015] or above the elbow [Chaeibakhsh et al., 2016]. The main goal of these studies is a long-term observation (sensors are worn during the period of one to three days) and quantitative evaluation of the difference between affected and healthy limb. The results are promising in both aspects. The authors underline the benefit of sensor data towards objective evaluations, as well as the good correlation with clinical scales. However, none of the previous studies deal with the MPIs that we propose in this thesis for the quantification of the arm/hand movements. Some examples of rehabilitation systems that include Myo armband device are described in [Qamar et al., 2015; Mithileysh and Sharanya, 2016; Ganiev et al., 2016; Rahman and Hossain, 2016], but only a few studies focus on the specific case of stroke [Lipovskỳ and Ferreira, 2015; Oboe et al., 2016; Liu et al., 2016; Holmes et al., 2016; Hidayat et al., 2016]. Lipovský and Ferreira [Lipovskỳ and Ferreira, 2015] proposed self hand-rehabilitation system using the Myo armband device and robotic glove. They designed a virtual reality game for the hand therapy. However, the study presents only the system architecture and lacks the system validation i.e. testing with patients. The authors in [Oboe et al., 2016] propose the robot rehabilitation system controlled with EMG signals. The focus is on the finger rehabilitation, particularly for patients who

cannot generate finger force. They use the EMG signals to obtain an estimate of the actual force exerted by the hand. They have proved that EMG levels are almost synchronized with the force. The patient controls the EMG level, and after a certain EMG threshold, the robotic hand performs the actual task that requires force. However, they compare the force and EMG signals by visual inspection. The movement analysis has not been performed in the study, neither the quantification of EMG signals. Similar like [Oboe et al., 2016], the study [Liu et al., 2016] addresses the control of the robotic arm, based on the IMU and EMG data. The focus is on the rehabilitation of upper body movements after stroke. The main goal of the paper is to map the upper limb motion to the robotic arm. Consequently, calculated measurements from the sensor data relate to the arm position and orientation angles, so the movement can be transferred to a robotic arm. In [Holmes et al., 2016] the authors propose a virtual reality rehabilitation system, intended for upper arms and body motion. The system consists of a Kinect v2, a Leap motion sensor and a Myo armband device. However, only the system design is presented, along with the general technical details. The system is preliminary tested in healthy subjects and the results are presented as outputs of the questionnaires. Although promising, the system still requires upgrades and validation with stroke patients. The authors in [Hidayat et al., 2016] use the therapy glove with bend sensors and Myo armband device to categorize the hand movements in the six descriptive categories (from the worst performance towards the best). For this purpose, they use only the direct sensor outputs without any processing procedure and extracting the meaningful descriptors.

To summarize, the latest studies present mainly conceptual Myo-based systems for stroke rehabilitation and evaluation of the patients' progress. The authors propose various system structures including either only Myo armband device or combining it with other sensor devices, such as Kinect or Leap motion. The majority of the proposed systems lack the experimental evaluation and verification with patients. Additionally, the reports on the quantification of the Myo sensor signals are quite poor. Some studies concentrate on the robot arm control for the hand rehabilitation, based on the EMG data. Those studies propose particular quantitative measurements that are mostly focused on the arm position and orientation angles, so the movement can be mapped to the robot arm. Clearly, strong time-frequency signal analysis and quantitative measurements are needed to support clinical decisions and evaluations during progress monitoring of the stroke patients.

We design combined vision and wearable system, based on the Kinect and Myo armband device. Furthermore, we develop the comprehensive approach to characterize the patients' movements based on the collected sensor data. We propose novel scores, Movement Performance Indicator (MPI) that can be used by therapists for evaluations of the patients' condition during the post-stroke period. Finally, we build an application for storing, visualization and interpretation of the collected sensor data and MPIs.

The application contains personal patients' profiles, along with their relevant clinical and sensor data over time. Thus, physiatrists can have the unified evidence about patients' progress. Additionally, personal profiles bring us closer to the concept of home rehabilitation. In the future, patients will practice at home, while their records will be sent directly to physiatrists using the application and cloud computing.

Chapter 3

Quantitative assessment of the full-body movements in Parkinson's disease using Kinect device

Impairments of the gait and large range upper body movements are often the first indicators of motor dysfunctions in general. In neurological disorders, the assessment of the large range movements' performance is usually the initial step towards a preliminary evaluation of the patient condition. Conventional evaluation techniques rely on the clinical assessment tools i.e. specially designed clinical tests and scales. Clinical scales are descriptive and offer limited possibilities for assessment of the patient condition. The widely used clinical scales for Parkinson's disease (PD) [Jankovic, 2008] assessment are Hoehn and Yahr (HY) [Goetz et al., 2004] and Unified Parkinson's Disease Rating Scale (UPDRS) [Goetz et al., 2008]. According to the HY scale, patients can be assigned into one of the five levels in total. UPDRS scale has more levels and decisions are made based on the evaluation of different aspects such as gait, upper body and hand movements, balance, posture and stability, even the facial expressions and speech. Even if the UPDRS scale is more informative than HY scale, decisions are still prone to subjective evaluations, which can lead to the imprecise interpretation of the patient's state.

Therefore, there is a clear need for introducing new techniques into the clinical practice, capable to enhance the evaluation procedures in PD and neurological disorders in general. In order to support the doctors' evaluations and to verify their decisions, an objective approach based on the quantitative measurements needs to be introduced.

The new generation sensing devices, such as Kinect device, open the possibility for affordable, non-invasive and reliable evaluation of the gait and large range upper body

movements. Kinect has a built-in algorithm for human skeleton detection and tracking. The 3D coordinates of the fifteen characteristic skeleton joints are collected for every frame during the movement performance using the marker-free based technique. In this chapter, we will explain how the sensor data collected using Kinect device can be processed towards quantitative measurements of the movement performance. In collaboration with the medical domain experts, we design quantitative movement scores called Movement Performance Indicators (MPIs) that can be used to support clinical evaluations. The designed MPIs can be classified into two groups: (i) MPIs well-known in medical practice assessed by obsolete (imprecise) techniques and (ii) newly-proposed MPIs, suggested by the doctors, that cannot be observed using conventional techniques. The movement speed and the range of motion belong to the first group, while the rigidity measure and symmetry ratio represent newly-proposed MPIs. The symmetry ratio has been widely used as a validity criterion for models in biomechanics and motor control [Plamondon, 1995; Gribble and Ostry, 1996]. In fact, it has been shown that the symmetry of kinematic speed profiles is an exclusive result of neurological mechanisms [Bullock and Grossberg, 1991; Mirkov et al., 2002], without any interference from changes of conditions or variables of the performed task. We describe how the proposed MPIs can support the clinical evaluations. The decision-making sheme is build using corresponding classifiers, based on the extracted MPIs. However, since the upper-body movements can give only the general insight about patients' condition, the successful classification was performed between patients and controls, as a support to diagnosis task. For a more detailed analysis and evaluation of the disease stage, assessment of the arm/hand movements is necessary and it will be the subject of the following chapters (Chapter 4 and Chapter 5).
Finally, in the scope of this chapter, we propose the novel approach for the movement segmentation.

3.1 Proposed system structure

The proposed system structure for quantitative assessment of the full-body movements using Kinect device is illustrated in Figure 3.1.

The Kinect is a low-cost motion sensing device that offers a suitable alternative to more expensive and complex vision-based motion capture systems, used today in the rehabilitation practice. The process of the data acquisition is based on the visual skeleton tracking and collecting the 3D positions of characteristic joints without markers. The maximum frame rate for the Kinect is 30 frames per second (30 Hz), but in our case due to additional processing required by data collection, the frame rate drops down to 27 Hz. The acquired data consist of 3D positions of characteristic skeleton joints, along with RGB and depth video sequences (Figure 3.2). The experimental protocol is explained in detail in Section 3.2.

Before the movements acquisition, the Kinect device is calibrated by performing a specific calibration body pose. As a second stage, the sensors signals are pre-processed with low-pass filters aiming at reducing measurement noise. A temporal segmentation algorithm is applied to the Kinect sensor signals since the movements are collected in the sequence, but each movement has to be analyzed separately. We propose two segmentation algorithms: (i) approach based on the local maxima and minima (Section 3.3.1) and (ii) predictive event based approach (Section 3.3.2). The MPIs design is detailed in Section 3.4. For characterizing the full-body movements, 10 MPIs have been adopted. In order to reveal which MPIs are the more relevant and informative, as well as to design the reduced MPI set, we have further performed dimensionality reduction procedure based on the Linear Discriminant Analysis (LDA) approach (Section 3.5.2). Finally, classifiers are designed as decision-making systems to support diagnosis evaluations based on the proposed MPIs (Section 3.5.3).

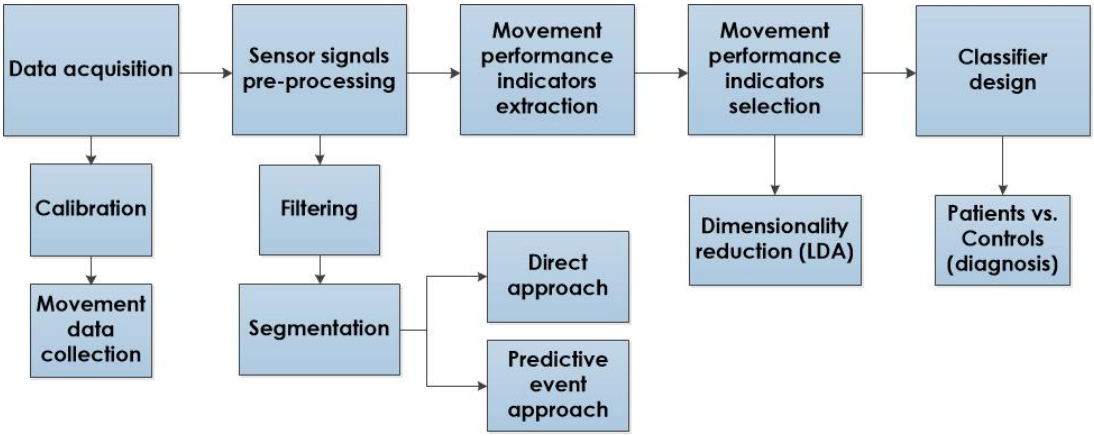


Figure 3.1: Proposed system structure

3.2 Experimental procedure

3.2.1 Participants

The experimental group consists of twelve PD patients with personal and disease characteristics listed in Table 3.1. We focus on the PD patients from I to III disease stage according to modified HY scale. The patients at advanced stages of PD (IV/V modified HY scale) are not able to carry out the sensor measurements, due to the severe motor impairments and functional handicaps. In addition, the movement quantification and inclusion of sensor measurements as a support to clinical evaluations is more of interest in the earlier disease stages.

A control group is formed by twelve subjects without any history of neurological or movement disorder. All subjects have been examined under the same conditions and they have performed the gait test and three upper body movements (Figures

3.2). The experimental exercises are well-known in the rehabilitation practice and can be particularly relevant for the evaluation of PD rigidity and bradykinesia symptoms [Jankovic, 2008; Goetz et al., 2008].

Table 3.1: Patient characteristics

Age (years), mean (SD)	60.33 (7.76)
Range	50-73
Gender (number of patients)	Males (10)
	Females (2)
Modified Hoehn and Yahr (HY) stage, mean (SD)	2.08 (0.79)
Range, 1-5	1-3
UPDRS motor score (section III), mean (SD)	29.92 (11.61)
Range, 0-108	13-48
Duration of PD (years), mean (SD)	3.42 (3.40)

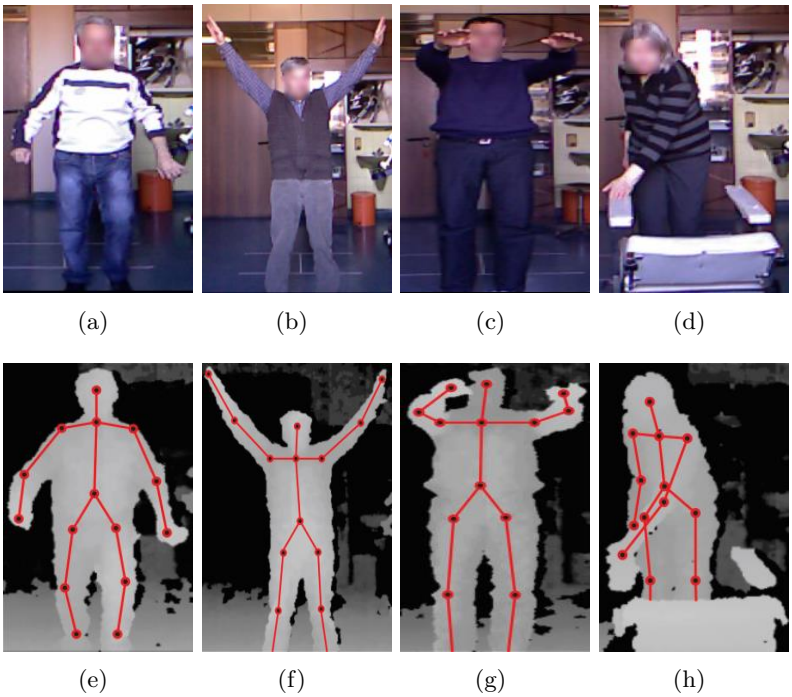
3.2.2 Experimental protocol

Following the therapist advice, all rehabilitation exercises are designed to recover or enhance one of the three main human functionalities – balance, mobility in the sense of normal gait and upper body movements [Keus et al., 2007]. The gait test is fairly present in the majority of rehabilitation procedures and it can have different forms depending on the equipment used and the measured gait performance indicators/features [Clark et al., 2012]. In this work, the gait test is carried out in accordance with the available Kinect range [Clark et al., 2012], with the starting and end points placed at 3.5m and 1.5m away from the Kinect, respectively. During the gait test, patients walked the selected distance of 2m six times with normal and natural gait rhythm (Figure 3.2(a)). The rest of the tested exercises belong to a group of upper body movements: Shoulder abduction-adduction (SAA) (3.2(b)) until maximum possible range of motion, Shoulder flexion-extension (SFE) (Figure 3.2(c)) and movements of the right-left hand between the boundaries (further, Hand boundary movements (HBMs) , Figure 3.2(d)).

In our experiments, all signals were filtered with Butterworth low-pass filter (BWLP) that proved to be effective in terms of noise removal. Cut-off frequencies and order of the filter were chosen in accordance with the signal sampling rate and the frequency characteristic of the meaningful signal content.

3.3 Temporal segmentation

Sensor motion data are collected in a sequence of several consecutive repetitions of the instructed movement. Since the MPIs for Kinect data are extracted from each movement separately, a temporal segmentation algorithm is applied to divide the sequence into the corresponding movement segments. On the other hand, the data glove and



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 3.2: RGB stream (a-d) and depth stream from Kinect with detected skeleton and collected joints (e-h)

Myo MPIs are extracted at a time for all movements in the sequence; hence segmentation algorithm is applied only to the Kinect data.

3.3.1 Temporal segmentation based on the local maxima and minima

The first segmentation algorithm is based on the analysis of the relevant joint for each specific movement and detecting its meaningful positions along the particular axis of interest. In other words, joint positions can reveal the movement's starting and termination frames. Let the observed skeleton data be represented by:

$$[J_1, ..., J_n, ..., J_N] \in R^{3K \times N}, 1 \leq n \leq N \tag{3.1}$$

where N is the total number of frames, K is the number of collected joints per frame ($K = 15$) and

$$J_n = [j_1^{v_{n,1}}, ..., j_k^{v_{n,k}}, ..., j_K^{v_{n,K}}] \in R^{3K \times 1}, 1 \leq k \leq K, j_k^{v_{n,k}} = (x_k^n, y_k^n, z_k^n) \in R^{3 \times 1} \tag{3.2}$$

where J_n represents the set of all K collected joints per frame n and $j_k^{v_{n,k}}$ particular $k - th$ 3D-coordinate joint in the frame n. Our goal is to find a set of vectors (Eq. 3.3):

$$V = \{[s_1, t_1], ..., [s_l, t_l], ..., [s_L, t_L]\}, 1 \leq l \leq L \tag{3.3}$$

where L denotes the total number of movements (temporal segments) in a sequence and each vector consists of two components: the first one represents the starting frame (sl) and the second one corresponds to the termination frame (tl) of the $l-th$ movement.

The segmentation algorithm is based on the search for "peaks" and "valleys" in the input signal, i.e. local maxima or minima. Input signal represents the evolution of the chosen joint in the direction (x, y or z, Figure 3.3) with the most expressed transitions during the particular movement. Under the gait test, it is the evolution of the torso joint in the z-axis direction. As for upper body movements, right-hand joint in the y-axis direction was chosen for shoulder abduction-adduction (Figure 3.3) and flexion-extension movement, while the both hand joints in the x-axis direction represent the input signals of the segmentation algorithm for hand boundary movement sequence. Segmentation points are extracted from the determined set of local minima and maxima points. Then, the actual beginning and end of the movements are isolated based on the two types of threshold conditions: (i) amplitude value threshold (amplitude range in which segmentation points lie) and (ii) temporal position threshold (corresponding distance in time between the points of interest must be satisfied). Threshold values are established depending on the particular movement and its temporal evolution in the selected direction. Figure 3.3 illustrates the segmentation algorithm for the case of shoulder abduction-adduction movement sequence. Evolution of the right-hand joint in the y-axis direction shows that y value increases from the starting position in the first part of the movement (when the arms go up) and then decreases in the second part of the movement (when the arms go down). The actual starting and ending points for all six movements in the sequence are correctly determined by our segmentation algorithm (Figure 3.3).

3.3.2 Predictive event approach based temporal segmentation

The predictive event approach is based on a principle of detecting an event when sensor data depart significantly from an adaptive model-based predictor. During the exercise execution, the skeleton is continuously detected and 3D positions of characteristic human joints are collected for each frame (Figures 3.2). For the verification of the segmentation approach, we use the sensor data for three upper body movements, excluding the gait test. From the original data set, which consists of all collected joints motion data, we have extracted the ones from interest for upper body movement therapeutic exercises (hand and elbow joint). Trajectories of selected joints are modelled as Gaussian processes. Based on this data set, a Gaussian process based predictor is adapted and used to detect significant changes in the exercise sequences. The results

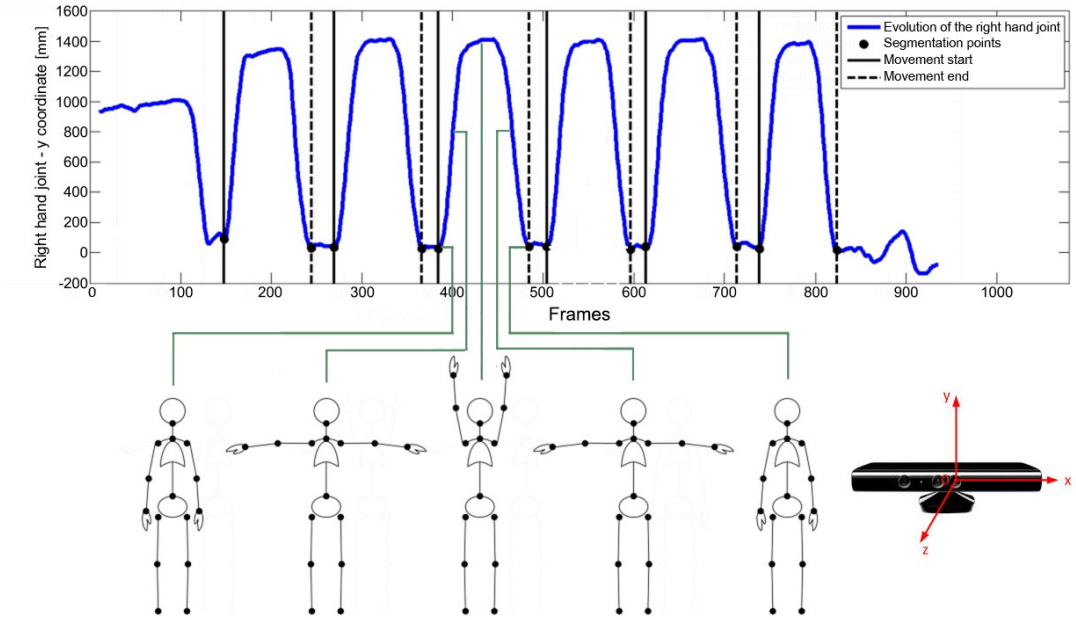


Figure 3.3: Illustration of the segmentation approach Shoulder abduction-adduction (SAA)

over the formed dataset are compared with commonly used technique and illustrate the superiority of the proposed approach. Trajectories of elbow and hand joint positions are modelled as Gaussian processes and three predictive Gaussian prediction model (each model for one coordinate) are formed. Number of hypereparameters which define the meaning and covariance functions of Gaussian process depends on the form of input and output training set samples. Let n be the number of frames in the exercise sequence and x_i value of x-coordinate in $i-th$ frame. Training input set (Eq. 3.4) consists of samples that are organized as k-dimensional vectors:

$$X = ([x_1, ..., x_k]; [x_2, ..., x_{k+1}]; ...; [x_{n-(k-1)}, ..., x_n]) \tag{3.4}$$

Training output set (Eq. 3.5) contains from following scalar samples of appropriate training input vector sample:

$$X_* = (x_{k+1}; x_{k+2}; ...; x_n) \tag{3.5}$$

This procedure is repeated analogously in the case of the input and output training set for y coordinate, Y and Y*. Given this data set, corresponding mean functions of Gaussian models have per k, and covariance functions per two free parameters, which are determined in the process of hyperparameters optimization. Predictive models are defined using input and output training and input testing set, obtained hyperparameters and selection of appropriate inference method. Models are formed for x and y trajectories of hand joints, since the exercises are performed in x-y plane. The values of

the z-coordinate in this case did not give any contribution to the final result; therefore they are not taken into account.

Errors of prediction in the form of the difference between real (x, y) and predicted values ($\hat{x}$, $\hat{y}$) are calculated at each step. Since the Gaussian process based predictor predicts both, mean and variance, in order to obtain a normalized distance metric, Mahalanobis distance (Eq. 3.6) is also calculated at each step. Using this metric, the method is more sensitive to small errors if a data point has high certainty.

$$MD = \sqrt{\begin{bmatrix} x - \hat{x} & y - \hat{y} \end{bmatrix} \begin{bmatrix} \sigma_x & 0 \\ 0 & \sigma_y \end{bmatrix}^{-1} \begin{bmatrix} x - \hat{x} \\ y - \hat{y} \end{bmatrix}} \tag{3.6}$$

where σ_x and σ_y are predictive variances for first and second Gaussian predictive model, respectively.

We have observed changes of the Mahalanobis distance through sequence of movements. When Mahalanobis distance increases significantly for several successive time steps and then drops again, boundary points of that segment are marked as events. In our case, events represent potential start and end of the movement. Mahalanobis distance for one sequence of exercises is shown on the Fig. 3. Peaks that have the greatest values represent points in the sequence where the values of x and y hand coordinate suddenly increase or decrease. More precisely, positions where Mahalanobis distance has greater value than a determined threshold (Fig. 3.4) are marked as events. As the threshold varies, positions and numbers of events are changing and this is the only parameter that is necessary to adjust. The hand trajectory of true and predicted x and y coordinates of hand joint together with detected events for k=5 (Eq. 3.4 and 3.5) are shown on Fig. 3.5.

Fig. 3.4 shows that detected events correspond to the characteristic points in the sequence where the values of x or y coordinate of hand joint start or stop to change significantly. In order to keep only the events with a meaningful information (real beginnings and ends of individual exercises), we take into account the time occurrence of the events and the time difference between the events of the interest. The proposed approach is compared with standard technique for detecting characteristic or extreme points in the sequence – technique of the first derivative. Comparison of these two methods (Fig. 3.6) is based on the combined sensitivity and specificity criteria (Eq. 3.7, 3.8 and 3.9), commonly used statistical tool for measuring classifier performance [Sokolova and Lapalme, 2009]. Value P (y-axis on Fig. 3.6) is calculated using relations (Eq. 3.7, 3.8 and 3.9) for different values of the threshold in the case of five exercise sequences.

$$P = \sqrt{sens \cdot spec} \tag{3.7}$$

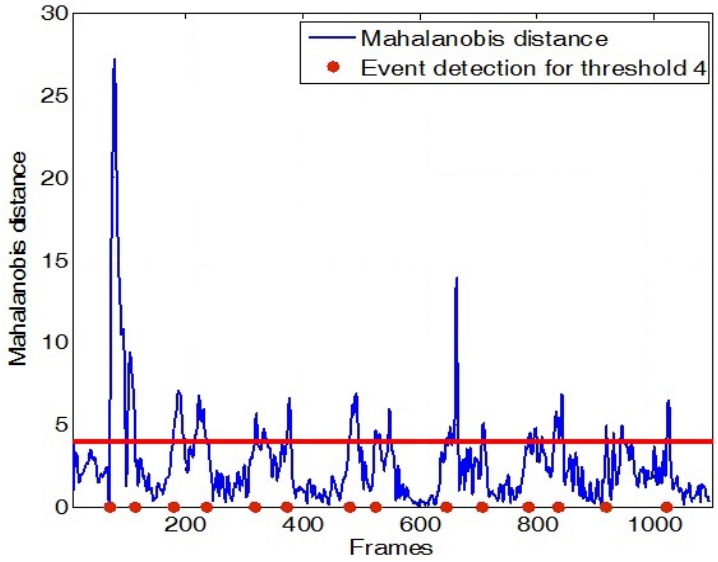


Figure 3.4: Mahalanobis distance with event detection

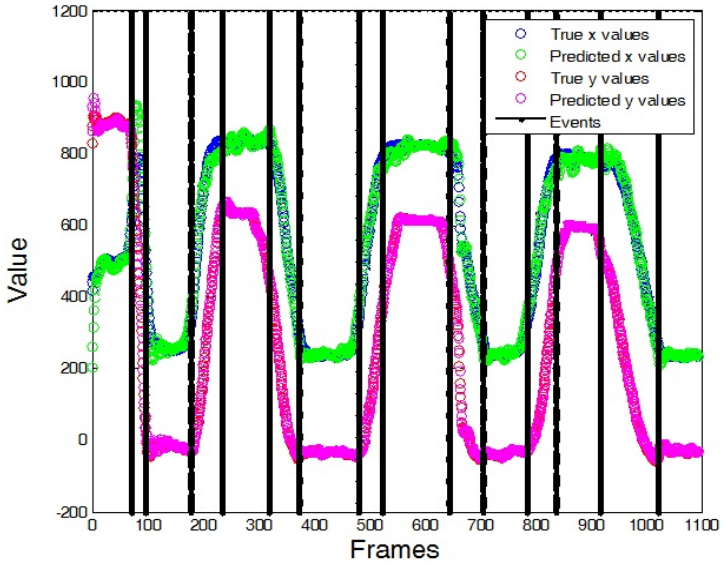


Figure 3.5: True and predicted values with detected events

$$sens = \frac{TP}{TP + FN} \tag{3.8}$$

$$spec = \frac{TN}{TN + FP} \tag{3.9}$$

In relations 3.8 and 3.9, TP denotes the number of true positives, FN the number of false negatives, TN the number of true negatives and FP the number of false positives. According to the form of Eq. 3.7, 3.8 and 3.9, it can be seen that greater values of sensitivity and specificity indicate better performances of the approach, hence figure 5

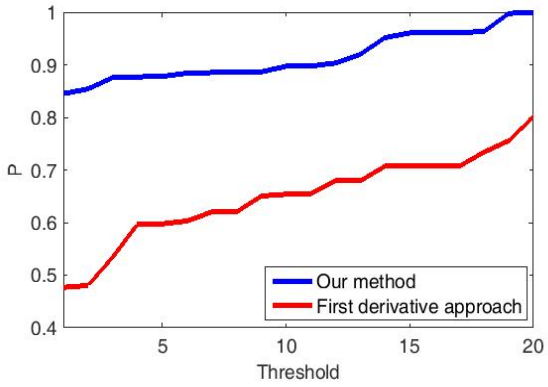


Figure 3.6: A comparison of our method and first derivative approach based on the sensitivity and specificity criteria

clearly illustrate the superiority and advantage of our approach. Using this approach, we have confirmed the results of the segmentation procedure based on the maxima and minima, previously presented in the Section 3.3.1.

3.4 An approach to movement characterization

We have used several MPIs to represent the full body movements acquired using the Kinect. The choice of MPIs was partly resulting from discussions with doctors, therapists, and other domain experts. In the following section, we will detail how these MPIs were designed. All together we have used 10 different MPIs that result from the combination of four measurement categories (Speed, Rigidity, Range of Motion (ROM) and Symmetry (Symmetry Ratio (SR)) applied to 4 categories of full-body movements, as illustrated in 3.2.

Table 3.2: The proposed MPIs result from a combination of 4 body movements and 4 MPI categories (speed, rigidity, ROM and symmetry (SR))

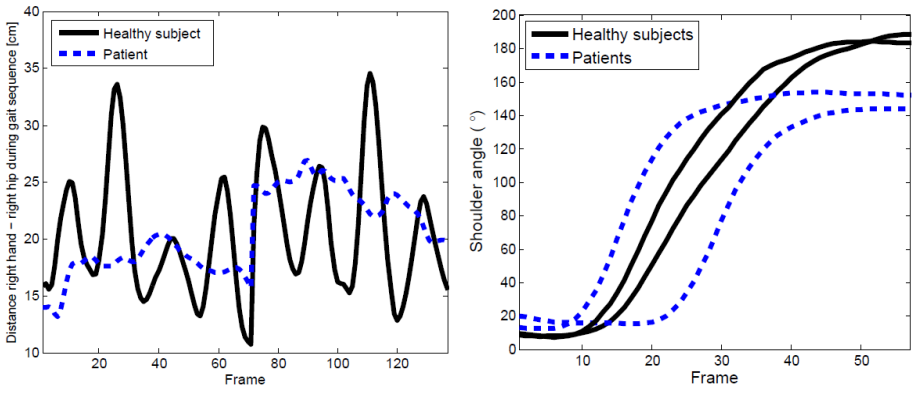
Movements / MPI categories	Speed / Speed variations	Rigidity	ROM	SR
Gait	• MPI_1 / MPI_2	• MPI_3		
SAA	• MPI_5		• MPI_4	• MPI_6
SFE	• MPI_8		• MPI_7	• MPI_9
HBM	• MPI_{10}			

The MPIs we extracted from gait movements are commonly used in the rehabilitation practice and treatment [Shima et al., 2008]. From gait movements, we considered three MPIs – speed of the gait, variations in the gait speed and hand rigidity - during walking. We have adopted the mean gait speed V, Eq. 3.10, during each two-meter sequence. Due to possible deviations of the starting and end point of the gait test, and in order to improve the accuracy, the path length (the numerator in Eq. 3.10) has

been calculated as the total trajectory of the torso during each gait sequence, instead of setting the path length of 2m. The total trajectory length is obtained by summing up the Euclidean distances (d) between the torso joint coordinates $X_i(x_i, y_i, z_i)$ and $X_{i-1}(x_{i-1}, y_{i-1}, z_{i-1})$ for consecutive frames, i and $i-1$, during the gait sequence. The time duration of the gait sequence (the denominator in Eq. 3.10) is computed based on the total number of frames (m and n denote respectively the first and last frame of the sequence) and the frame rate, $f = 27Hz$.

$$V = \frac{\sum_{i=m}^{n} d(X_i, X_{i-1})}{(n - m + 1)/f} \tag{3.10}$$

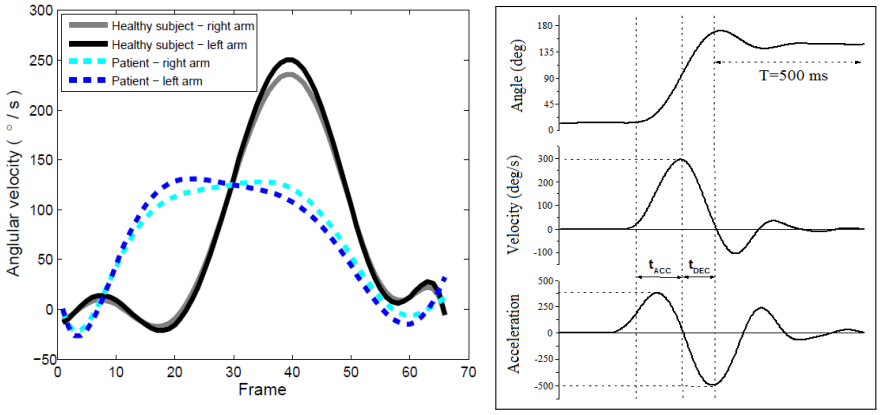
Variations in the gait speed are calculated as the differences in the gait speed between each two consecutive 2-meters gait sequences. This MPI can be an indicator of the unbalanced gait if the speed value significantly differs from one gait sequence to another. The position of the arms during walking can reveal rigidity, one of the main indicators of the PD [Jankovic, 2008]. In the case of healthy subjects, the arms usually swing in a certain rhythm during gait activity, in contrast to the Parkinson's patients. We have computed a measure of rigidity, based on the hand position during the gait test. The rigidity symptom can be noticed in the variation of the distance between the hip and hand during the gait sequence. For healthy subjects, the temporal evolution of these distances is approximately periodic, due to normal arm swing. In contrast, for patients with one rigid arm, the distance between the rigid hand and the closest hip does change significantly over time (Figure 3.7(a)). The measure of rigidity is calculated in two steps. First, we record the difference signal between the left and right hand-hip distances, during the gait movement. Then, we take the highest value of the (absolute) difference signal as an indicator of rigidity.



(a) (b)

Figure 3.7: (a) The difference between the left/right hand-hip distances shows the rigidity symptom. (b) Evolution of the shoulder angle profiles during shoulder abduction movements.

For patients with a rigid arm the difference signal is larger because the healthy arm performs a normal swing and the rigid arm remains more or less static. Instead, healthy subjects display a lower-amplitude difference signal, due to the normal swing of both hands. Inspired by the well-known and widely used rehabilitation measure for upper body movements, we have also computed the ROM [Keus et al., 2007] for the SAA and SFE exercise. The ROM represents an angle of the movement relative to a specific body axis, which can be measured at various joints such as elbow, shoulder, knee, etc. In our case, we measure the evolution of the shoulder angle during the movement in relation to the longitudinal body axis. As a specificMPI, we have used the ROM (maximum achieved shoulder angle). Examples of the shoulder angle profiles of both normal subjects and patients for the shoulder abduction movement are shown in Figure 3.7(b). The ROM is higher for healthy subjects (more than 180°) than for patients (142°, 150°). In addition, the trajectory of shoulder angle is steeper for healthy subjects, indicating a higher speed of movement. We calculated the mean movement speed for all three tested upper body exercises. The applied procedure was the same for the gait speed (Eq. 3.10), setting the path length to the total length of hand trajectory during the movement. The comparison between relevant left/right body-side movement descriptors can suggest which side or limb is more affected by the neurological disorder. For healthy subjects, these differences are usually negligible, while they can become quite large for Parkinson's patients, depending on the disease stage. Important movement descriptors such as profiles of joint angles (Figure 3.7(b)) and angular velocity profiles (Figure 3.8(a)) can reveal the symmetry of the movements. In order to quantitatively assess the movement symmetry, we have extracted Symmetry Ratio (SR) from the shoulder abduction-adduction and shoulder flexion-extension exercises. In motor control, the SR [Plamondon, 1995; Gribble and Ostry, 1996; Bullock and Grossberg, 1991; Mirkov et al., 2002] (Figure 3.8(b)) is defined as the ratio between acceleration (t_{ACC}) and deceleration (t_{DEC}) times, during one movement. Figure fig:fig8a shows that the maximum angular velocity of the shoulder abduction movement is higher for healthy subjects than it is for Parkinson's patients. In addition, healthy subjects reach the maximum angular velocities of the left/right arm movements approximately at the same time as opposed to non-healthy subjects, where a difference of about 20 frames is typical. The consequence is unbalance in symmetry ratios between left and right arm for the same movement. Thus, in our experiments, we obtained larger left-right differences of the symmetry ratios for Parkinson's patients than in healthy subjects.
We have described 10 MPIs extracted from the Kinect data to quantify the full body movements. These MPIs will be used later on for a classifier design to support the diagnosis evaluations in PD.



(a) (b)

Figure 3.8: Evolution of the shoulder angular velocity profiles during shoulder abduction movements (a) and symmetry ratio calculation (b)

3.5 Results

We have defined a set of 10 MPIs to characterize the full-body movements that can be used for diagnosis support of the PD during rehabilitation. The design of these MPIs was grounded on the information provided by neurologists and therapists with the goal of delivering quantitative information about subject's performance. In this section, it will be shown how these MPIs can be successfully used in practice. When dealing with the established MPIs set, three important questions are imposed: (1) What is the internal consistency of the sensor measurements and reliability of the extracted MPIs? (2) Which MPIs are the more relevant and informative? (3) Can we improve classification results if we design an optimized MPIs set? To answer the first question we conducted the statistical analysis. To investigate questions 2-3 we adopted a Linear Discriminant Analysis (LDA) approach [Fisher, 1936].

3.5.1 Internal consistency of the sensor measurements and reliability of the extracted MPIs

Internal consistency of the sensor measurements is assessed using Cronbach's alpha parameter [Field, 2009]. In the case of the Kinect sensor measurements, Cronbach's alpha parameter was investigated for four recorded movements, fifteen collected joints (Figure 3.2) and three coordinates (X, Y and Z, Figure 3.3). The data set for internal consistency analysis consists of six patients with repeated Kinect measurements (measurements repeated within one week). All obtained Cronbach's alpha parameters across different movements, joints and coordinates for the six patients data have values within the range $[0.95 - 0.99]$. Values of Cronbach's alpha parameter close to one indicate the high consistency of the Kinect sensor measurements.

In order to test the reliability of the extracted MPIs, the split-half method for

reliability analysis [Field, 2009] has been applied. This method takes into account all patients and healthy subjects data, in contrast to the standard approach of the test-retest reliability, that can include only the subjects with repeated measurements. The split-half method divides the conducted tests into two parts and correlates the scores on one-half of the test with scores on the other half of the test. Thus, the split-half method estimates the reliability based on the repetitions inside the same trial. Reliability of the extracted MPIs from the Kinect data is assesed using Intraclass correlation coefficient (ICC) [Field, 2009]. ICC has a value inside range [0 - 1], whereby the values closer to 1 indicate higher reliability. Reliability results are shown in the Table 3.3, along with the 95% confidence intervals (CIs).

Table 3.3: ICC reliability parameters for Kinect MPIs

Kinect MPIs	**ICC**	**CI**
1.	0.9433	[0.8890 – 0.9711]
2.	0.5907	[0.1973 – 0.7913]
3.	0.6532	[0.3198 – 0.8231]
4.	0.9634	[0.9283 – 0.9814]
5.	0.9656	[0.9326 – 0.9825]
6.	0.7390	[0.4882 – 0.8669]
7.	0.8074	[0.6222 – 0.9018]
8.	0.9539	[0.9096 – 0.9765]
9.	0.5144	[0.0477 – 0.7524]
10.	0.9189	[0.8410 – 0.9587]

The majority of the extracted MPIs have shown high reliability, exept Variations in the gait speed MPI and Difference between right and left SR (SFE) MPI, where the values of ICC are less than 0.60. For the association between MPI numbers from Table 3.3 and corresponding MPIs please refer to Figure 3.9.

Figures 3.9 provide additional insight concerning full-body MPIs, and their ranges across patients and controls. MPIs 3, 4, 5, 7, 8 and 10 are normalized due to their high values and in order of comparable representation with other MPIs. The values of the ROM and gait/movement speed are lower in the patient group, while the left-right arm differences of the SR, during shoulder movements, as well as variations in the gait speed, are much larger in patients, as expected.

3.5.2 Dimensionality reduction

By adopting the proposed MPI for the tested full-body exercises, we obtain a set of 10-dimensional feature vector (Figure 3.9), which can be used in a classification system to assist diagnosis. We applied Linear Discriminant Analysis (LDA) [Fisher, 1936] to transform the original data sets into a new, compact, lower dimensional space, and to determine the most relevant MPIs for the decision-making process (diagnosis sup-

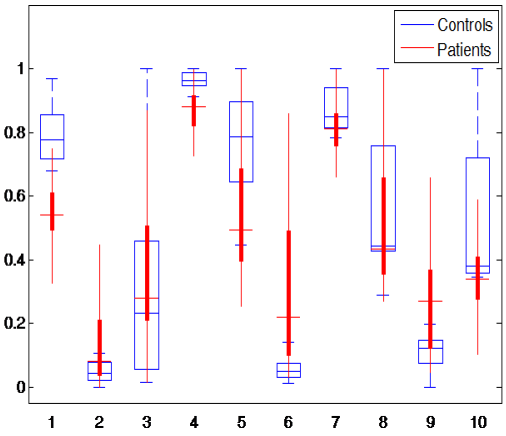


Figure 3.9: MPI ranges (Kinect data)

1. Gait speed [m/s]
2. Variations in the gait speed [m/s]
3. Rigidity measure [cm]
4. ROM (SAA) [°]
5. Speed (SAA) [m/s]
6. Difference between right and left SR (SAA)
7. ROM (SFE) [°]
8. Speed (SFE) [m/s]
9. Difference between right and left SR (SFE)
10. Speed (HBM) [m/s]

port). The LDA approach aims to maximize the between-class distance and to minimize within-class dissipation. The dimension of the newly created space is determined from the eigenvalues of the LDA criterion function, which takes into account the class covariances. Our tests revealed that the sum of the first two eigenvalues was much larger than the sum of the remaining eigenvalues ($\lambda_1 + \lambda_2 \gg \lambda_3 + \cdots + \lambda_m$), where m is the total number of features. Hence, we reduced the feature set to the new 2-dimensional feature space. As a side-result, the LDA method ranks the original features in terms of their contribution to the reduced feature space based on the weights ($v_{11}...v_{m1}; v_{12}...v_{m2}$) of the transformation matrix V, where m represents the total number of features, (Eq. 3.11). S is the matrix of the original data set with n samples while the L represents the matrix of reduced data set to 2-dimensional feature space.

$$L = S * V \Leftrightarrow \begin{bmatrix} l_{11} & l_{12} \\ \cdots & \cdots \\ l_{m1} & l_{m1} \end{bmatrix} = \begin{bmatrix} s_{11} & \cdots & s_{1m} \\ \cdots & \cdots & \cdots \\ s_{n1} & \cdots & s_{nm} \end{bmatrix} * \begin{bmatrix} v_{11} & v_{12} \\ \cdots & \cdots \\ v_{m1} & v_{m1} \end{bmatrix} \tag{3.11}$$

The modified informativeness index ($II(f)$) based on the weights of the transformation matrix is adopted for the first f features using Eq. 3.11:

$$II(f) = \frac{\sum_{i=1}^{f} |v_{i1} + v_{i2}|}{\sum_{i=1}^{m} |v_{i1} + v_{i2}|}, 1 \leq f \leq m \tag{3.12}$$

where the decreasing order of the sum of weights is considered: $(v_{11} + v_{12}) \geq (v_{21} + v_{22}) \geq \cdots \geq (v_{m1} + v_{m2})$.

The LDA method for groups of patients and controls results that, for keeping 80% of information from the original Kinect data set, it is sufficient to select the MPIs 1, 6, 9 and 10 from Figure 3.9. This result shows that, in addition to the speed of the gait and upper-body movement (HBM), both SR MPIs are amongst the most informative

MPIs. The LDA method also provides us with new synthetic features that form a reduced-dimension feature space. While these new synthetic features have the power to differentiate the different conditions in the data, they are less efficient in terms of communication and understanding for the medical doctors and therapists, as they do not correspond to a specific MPI.

3.5.3 Classification: diagnosis evaluations

So far, we have shown how to build a set of MPIs from the full body movements of Parkinson's patients. Statistical analysis confirmed the internal consistency of the sensor mesurements and reliability of the extracted MPIs. The LDA analysis has established a new reduced-dimension feature space and determined the most relevant MPIs. In this section, we present a classification approach that can automatically identify the different subject groups (patients vs. controls) based on the original and the derived feature sets. Using the Kinect data, we have tested the classification between healthy and non-healthy subjects in three different conditions: (i) with the original feature set, (ii) using the four most relevant features adopted in the previous section and (iii) the two new synthetic features, obtained from LDA. We have compared three different classifiers (Figure 3.10): (a) Support vector machines (SVM) with Radial basis function (RBF) kernel (bandwidth of the RBF kernel, σ and regularization parameter, C: $0.01 < \sigma < 1$, $0.01 < C < 10$), (b) K-nearest neighbors (KNN) (number of nearest neighbors, k $\in$ 1, 3, 5) and (c) neural networks (Multilayer perceptron (MLP): various structures with different number of hidden layers and nodes). The parameters of classifiers were chosen from listed ranges in a validation procedure in order to achieve the highest accuracy rate. Figure 3.10 shows that all classifiers succeed to differentiate healthy from non-healthy subjects. The SVM and the neural networks MLP have the best results when using the original feature set. The KNN classifier works best for the reduced feature sets but in general, is the least performing classifier. We achieve classification results close to 100%, compared to the chance level of 50%. The Kinect data showed poor results during classification between the disease stages. We achieved a classification accuracy of about 50%, compared to the chance level of 33%, which is not enough for evaluating the disease stage. Our results show that, while the Kinect MPIs have the power to distinguish patients from healthy subjects, the quantitative analysis of the disease stages requires more detailed and informative MPIs from the hand movements.

Even if the gait represents the most important motor task in general, to indicate the motor impairments, for the particular case of PD, patients at mild to moderate PD stages, do not experience significant gait disorders, contrary to the more advanced disease stages. By definition, serious gait disorders are starting at the third HY stage and become more important at fourth and fifth HY stages. Moreover, cardinal clinical

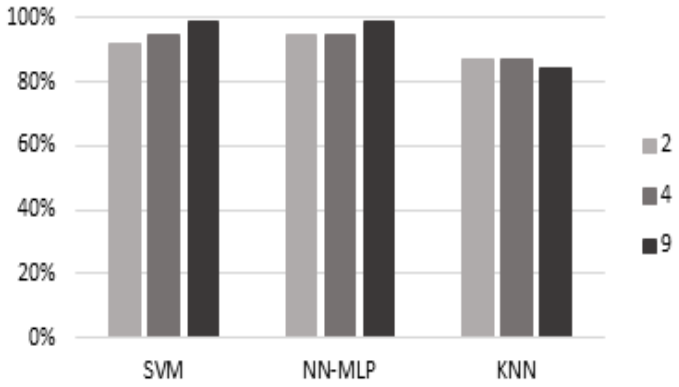


Figure 3.10: Classification accuracy of Kinect data (patients / controls)

symptoms such as bradykinesia, rigidity and later the hand tremor are required for establishment of the PD diagnosis, and those symptoms are continuously present at different disease stages. Hence, in the first three disease stages, hand movement behavior is also very relevant for PD assessment. Consequently, we have performed the quantification of the fine hand movements, as well, presented in the next Chapter 4.

3.6 Repeated experiments with Kinect

In order to investigate whether our proposed full body MPIs can keep track of the patients' performance over time in the same way as clinical measurements, we have conducted the repeated experiments of the tested full body movements. However, the MPIs extracted from the Kinect data have not demonstrated the capability to support clinical evaluations during the PD progress. The reasons for such outcome are the following: (i) Sensor data collected from the Kinect device are corrupted with noise and the precision of sensor readings is not high due to the low-cost device design. It has been shown that Kinect possesses a satisfactory accuracy for the application in the rehabilitation therapy [Khoshelham and Elberink, 2012; Clark et al., 2012; Chang et al., 2012]. However, this finding is valid for the rehabilitation therapy in general and it is applicable mainly to the movement tracking tasks. (ii) Gait and upper body movements give the general insight into the patients' state. For a more detailed analysis in PD, the examination of the arm/hand movement behavior is necessary, taking into account that the majority of PD symptoms is reflected in the arm/hand movements. The overall conclusion is that the Kinect-based MPIs can be useful for neurologists and therapists during the preliminary examination of the patient state. However, the clinicians cannot rely on the full body MPIs during their evaluation of the disease progress, as well as during determining the drug treatment. This conclusion is in accordance with the results from the previous Section 3.5.3, where we have showed that Kinect-based MPIs are not informative enough to successfully differentiate disease

stage groups.

3.7 Summary and discussion

We have presented an approach for therapeutic movement analysis relying on the low-cost vision-based device (Kinect), to support the traditional evaluation procedures for diagnosis purposes. Our results have shown significant differences between experimental (patients) and control (healthy subjects) groups for the proposed MPIs and the possibility of successful classification. For reducing the computational cost, we have applied a dimensionality reduction procedure and determined the most informative MPIs in terms of assisting the medical diagnosis process. This result underlines the significant role of new MPI we proposed – the symmetry ratio MPI for classification procedure. The main limitation of the approach results from the relatively modest accuracy of the Kinect and its inability for tracking finger joint trajectories without additional equipment. Another limitation is that the Kinect data are not informative enough for classification between the disease stages. Consequently, we have performed hand and fingers movement analysis, which is explained in the next chapter (Chapter 4). Finally, in the frame of the presented approach, we have proposed the method for therapeutic exercise segmentation based on a predictive Gaussian model and event detection principle. This approach has shown excellent results in the sense of correct detection of significant transitions during therapeutic movement performing and advantage in comparison with the commonly used technique of the first derivative.

Chapter 4

Quantitative assessment of the hand movements in Parkinson's disease using the data glove

In the previous chapter, we have presented an approach for quantitative assessment of the gait and large range upper body movements using the Kinect device. We have described the movements using relevant MPIs that turn out to be effective in distinguishing the controls and patients. As such, they can be used to support the clinical diagnosis evaluations in PD. The gait and large range upper body movements represent very important motor tasks to reveal the motor impairments. However, patients at mild to moderate PD stages, do not experience significant gait disorders, contrarily to the more advanced disease stages. By definition, serious gait and large range movement disorders are starting at the third HY stage and become more important at fourth and fifth HY stages. Moreover, cardinal clinical symptoms such as bradykinesia, rigidity and later the hand tremor are required for establishment of the PD diagnosis, and those symptoms are continuously present at different disease stages. Hence, in the first three disease stages, hand movement behavior is more relevant for PD assessment and monitoring of the disease progress than the gait and large range upper body movements. Furthermore, the MPIs proposed in the previous chapter are not informative enough to successfully address different disease stages and to support the clinical evaluations related to the monitoring of the disease progress.

In this chapter, we present the approach for quantitative assessment of the hand movements using the sensor glove device. For the hand movements acquisition, we use the Cyber Glove II device. This device is wireless, lightweight, adaptable for different hand sizes and suitable for inclusion in rehabilitation protocols. It outputs the joint angular data, that are further processed in order to obtain the relevant MPIs. Since the system is relatively costly, it has been tested as a proof of concept, towards the design of an affordable version of this data glove.

After the sensor data collection, the next challenge consists in defining suitable features (MPIs) that can be used to characterize the hand movements in the different subject conditions. The proposed MPIs are built upon domain-specific knowledge and provided by doctors and therapists as well as data analysis. We develop two different approaches for the extraction of the MPIs from the sensor signals. The first approach is the direct processing of the sensor signals in their original form (angular data) or modified form in the sense of signal derivarive (angular velocity data). Another approach includes the development of the hand model, that gives position information, important for the quantitative description of the hand movements. Hand model can be also used to visualize the hand movements and check whether the sensor data keep track of real finger movements within the appropriate range of motion. Finally, the thorough analysis of the proposed MPIs is conducted according to the following aspects of interest: (i) internal consistency of the sensor measurements and reliability of the designed MPIs; (ii) design of an optimized MPI sets relying on the dimensionality reduction and feature selection methods; (iii) classification between patients and controls and between disease stages (support to diagnosis and progress monitoring, respectively); and (iv) correlation with clinical scales (tapping test and UPDRS-III).

4.1 Proposed system structure

The proposed system structure for quantitative assessment of the hand movements using the data glove is illustrated in Figure 4.1.

The Cyber Glove II is a wireless, lightweight data glove, adaptable for different hand sizes and suitable for inclusion in rehabilitation protocols. The manufacturer's technical documentation reports sensor data rate up to 90 Hz and repeatability of 3 degrees. The glove has eighteen sensors giving joint-angle output – metacarpal and proximal sensors on each finger, four abduction sensors between each two consecutive fingers, wrist yaw and wrist pitch sensor placed on the hand wrist and sensors for measuring thumb crossover and palm arch (see Figure 4.2(e)).

The calibration procedure for the data glove consists of a predefined set of exercises to adjust initialization parameters. Signals from the data glove were noise-free. The MPIs are extracted from all consecutive movements in one sequence at the same time. Hence, the segmentation procedure is not a necessary pre-processing step, like it was the case in signals from Kinect. For characterizing the hand movements i.e. MPIs design (Section 4.3), two approaches have been developed: (i) direct extraction of MPIs from the sensors' signals (Section 4.3.1) and (ii) using a hand model to extract indirectly MPIs from the model, explained in a more detail in Section 4.3.2. Statistical analysis of the proposed MPIs has been conducted between groups of interest (patients/controls and the first three disease stages according to Hoehn and Yahr HY [Goetz et al., 2004]) (Section 4.4.2). The patients at advanced stages of PD (IV/V modified HY

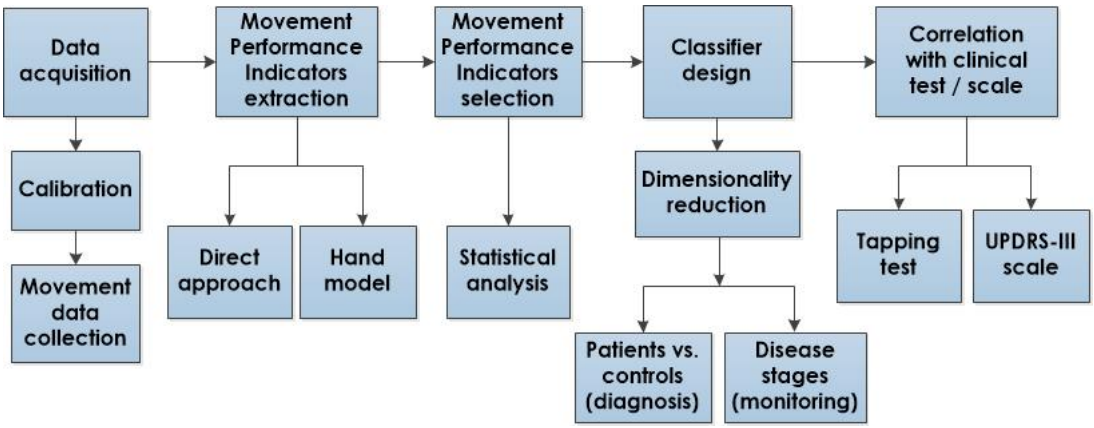


Figure 4.1: Proposed system structure

scale) are not able to participate in the experiments i.e. wear the sensor glove, due to the severe motor impairments and functional handicaps. In addition, the movement quantification and inclusion of sensor measurements as a support to clinical evaluations are more of interest in the earlier disease stages. Classifiers are designed as decision-making systems to support diagnosis and monitoring evaluations (Section 4.4.4) based on the original and reduced MPI sets (Section 4.4.3). Finally, correlation analysis between our proposed MPIs and clinical test / scale has been performed in Section 4.4.5.

4.2 Experimental procedure

4.2.1 Participants

The experimental group consists of twenty-four PD patients with personal and disease characteristics listed in Table 4.1. Similar like in the case of full body movements, we focus on the PD patients from I to III disease stage according to modified HY scale. Some patients have also performed the clinical tapping test. The number of patients per tests is also listed in Table 4.1. A control group is formed by seventeen subjects without any history of neurological or movement disorder. All subjects have been examined under the same conditions and they have performed four hand movements, instructed by a neurologist and therapists. The experimental exercises (Figure 4.2) are well-known in the rehabilitation practice and they are particularly relevant for the evaluation of PD symptoms such as tremor, rigidity, and bradykinesia [Jankovic, 2008; Goetz et al., 2008].

4.2.2 Experimental protocol

The medical procedure adopted in PD analysis includes a particular set of hand movements/exercises, in order to allow doctors to make a qualitative evaluation of the

Table 4.1: Patient characteristics

Age (years), mean (SD) Range	62.21 (8.80) 46-81
Gender (number of patients)	Males (19) Females (5)
Modified Hoehn and Yahr (HY) stage, mean (SD) Range, 1-5	2.25 (0.87) 1-3
UPDRS motor score (section III), mean (SD) Range, 0-108	32.08 (11.13) 13-57
Duration of PD (years), mean (SD)	5.75 (3.98)
Performed test (number of patients)	Data glove (24) Tapping test (15)

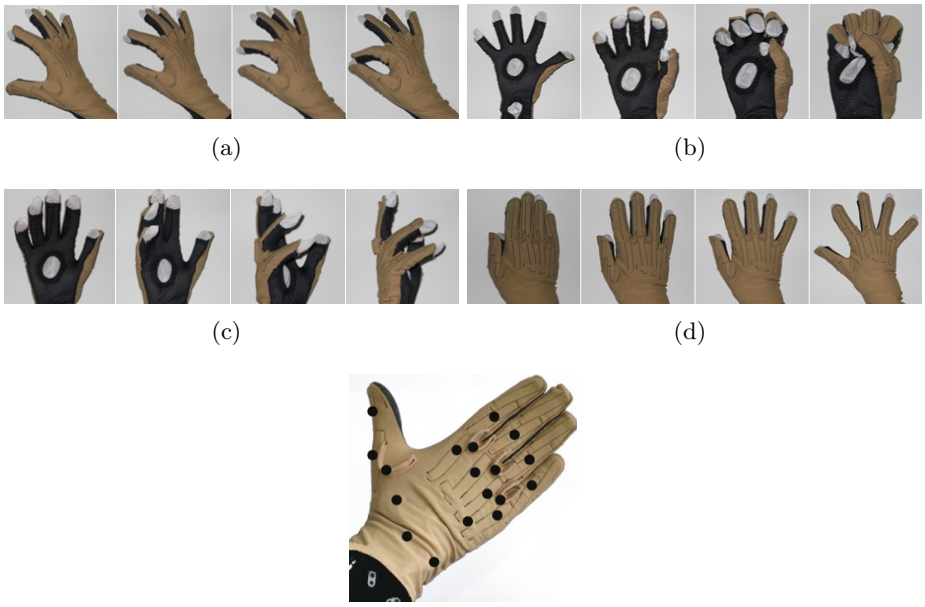
disease stage and progress. We examine four hand movements suggested by the medical doctors. The set of tested hand exercises is listed in the Table 4.2 and includes Finger-tapping movement (FTM) (Figure 4.2(a)), Fingers flexion and extension movement (FFEM) (Figure 4.2(b)), Rotation of the hand movement (ROHM) (Figure 4.2(c)), and Fingers expansion and contraction movement (FECM) (Figure 4.2(d)).

Table 4.2: Acquired hand movements according to the experimental protocol

	Acquired hand movements according to the experimental protocol
1.	Finger-tapping movement (FTM)
2.	Fingers flexion and extension movement (FFEM)
3.	Rotation of the hand movement (ROHM)
4.	Fingers expansion and contraction movement (FECM)

The total movements performance during the experiments was determined either by the time limitation (10 seconds for the ROHM or by the number of repetitions (twenty repetitions for FTM and FFEM and ten repetitions for FECM).

The clinical measurements (HY and UPDRS) are collected by one experienced rater immediately before the sensor measurements. All measurements have been performed in the hospital settings for outpatients. The clinician was present during the sensor measurements in order to monitor the patient state, and to prevent situations in which the patient is quickly switched from ON (the effect of medication present) to OFF state (the effect of medication stopped), due to which the possible clinical measurement and sensor measurement would be carried out under different conditions. The HY clinical values (which evaluate the disease stage) were assessed using the modified Hoehn and Yahr (HY) Scale [Goetz et al., 2004]. The UPDRS clinical values (which evaluate the motor symptoms) were assessed using the motor part of the Unified Parkinson's Disease Rating Scale (UPDRS) [Goetz et al., 2008].
Tapping test [Potter-Nerger et al., 2009] is frequently used by neurologists to examine hand movements in PD patients. The test consists of the proximal and distal tapping



(a) (b) (c) (d) (e)

Figure 4.2: Experimental exercises (a-d) and sensor positions on the glove (e)

Figure 4.3: Board for tapping test

tasks using a specially designed board (Figures 5.3) as the one proposed in [Potter-Nerger et al., 2009]. The proximal tapping task refers to the alternate pressing of two large yellow buttons located 20 cm apart with the palm of the hand. The distal tapping task is related to the alternate pressing of two closely located green buttons (3 cm apart) with the index finger while the wrist is fixed on the table. Both tests are repeated twice for the palm and index finger of the right hand, wherein each test lasts thirty seconds and the subject tries to alternately press the buttons as many times as possible. Since the data glove is designed for the right hand, only patients with affected right side (side on which PD symptoms are initiated) have been tested with the data glove.

4.3 An approach to movement characterization

Similarly to what we have done for full-body movements (Chapter 3), we propose a new set of MPIs to characterize the hand movements (Table 4.3) with respect to: (1) ROM of the characteristic hand and finger joints (for Fingers flexion and extension movement (FFEM), Figure 4.2(b)) and Rotation of the hand movement (ROHM), Figure 4.2(c)); (2) velocity values derived from abduction sensor angular data (for Fingers expansion and contraction movement (FECM), Figure 4.2(d)) and (3) velocity and acceleration parameters between thumb and index finger tips estimated from the hand model (for Finger-tapping movement (FTM), Figure 4.2(a)).

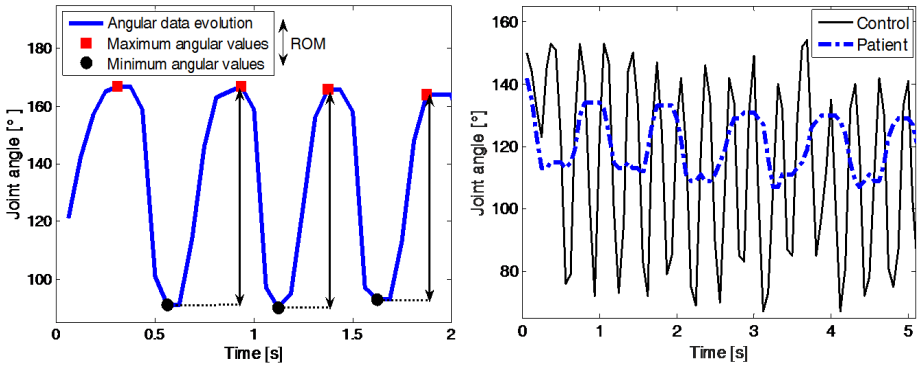
Table 4.3: Extracted MPIs from the collected hand movements

Movements	**FFEM**	**ROHM**	**FECM**	**FTM**
Extracted MPIs	Joints ROM: metacarpal and proximal joints	Joints ROM: wrist yaw and pitch	Angular velocity data: abduction sensors	Velocity and acceleration signal parameters
Sensors of interest				Hand model

4.3.1 Direct approach

The ROM of the hand and fingers characteristic joints can be derived directly from the sensor angular data signals. It is defined as the distance between the angular sensor values from the initial (minimum angular value) to the final position (maximum angular value) during each movement in the sequence (Figure 4.4(a)).

The ROM measurement is extracted from the FFEM and ROHM. The FFEM is representative in the investigation of the tremor, dyskinesia and the mobility of the fingers. Subjects are asked to perform twenty consecutive alternating FFEMs as fast as possible. For the quantification of this movement, we concentrate on the sensor data collected from metacarpal (index, middle, ring and little finger) and proximal finger joints (thumb, index, middle and ring finger) according to their high activity during movement performance (Table 4.3). The ROHM can indicate the presence and severity of the rigidity symptom. Under this movement's test, subjects need to rotate their hand to the left and right direction alternately as fast as possible during a ten second period. The relevant sensor data for this movement are collected from the wrist



(a) (b)

Figure 4.4: Calculating the ROM of finger joints (a) and evolution of the wrist yaw joint angular data profiles during ROHM (b)

yaw and wrist pitch position (Table 4.3). The angular data profiles of wrist yaw joint (Figure 4.4(b)) for control subjects show the expressed periodicity and wide range of motion. For patients, the range of motion is substantially smaller and the signal clearly illustrates the execution of slower movements (Figure 4.4(b)). The FECM tests the functionality, flexibility and speed of finger movements; hence, it can reveal the presence of asynchronous, uncoordinated motion and dyskinesia. Subjects are asked to perform ten consecutive FECMs. It is characterized using four abduction sensors, placed between each two consecutive fingers. The Angular velocity (AV) signals are derived from processed angular data since the velocity values have underlined greater differences between experimental and control group than ROM data. Maximum AV values for each movement in a sequence of both, expansion (Figure 4.5, control - green circles, patient - red circles) and contraction phase (Figure 4.5, control – green squares, patient - red squares) are extracted as MPIs. Evolution of the AV profiles of patient and control subject for ring-pinky abduction sensor is given in Figure 4.5. It can be seen that control subject's consecutive FECMs reach higher velocity values compared to the same movements in patients.

4.3.2 Model-based estimate of hand MPIs

Finger-tapping movement (FTM) is the most frequent rehabilitation exercise in the PD protocol, which tests symptoms such as tremor, dyskinesia, and bradykinesia. In our finger tapping test, subjects are directed to perform twenty consecutive touches between the thumb and index finger tips as fast as possible with the elbow fixed on the table. It has been widely studied and some attempts at its quantification are reported in [Okuno et al., 2006, 2007; Shima et al., 2008, 2009]. In some of these approaches, sensors are attached at the thumb and index finger tips making contact detections during the finger-tapping movement performance. In [Okuno et al., 2006, 2007] mea-

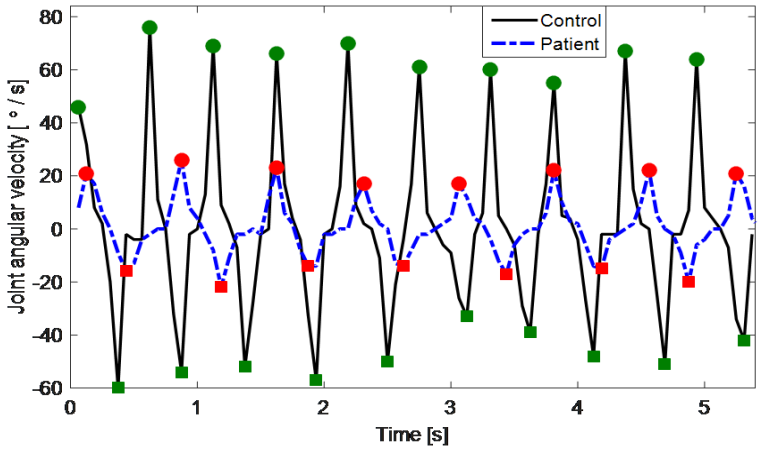
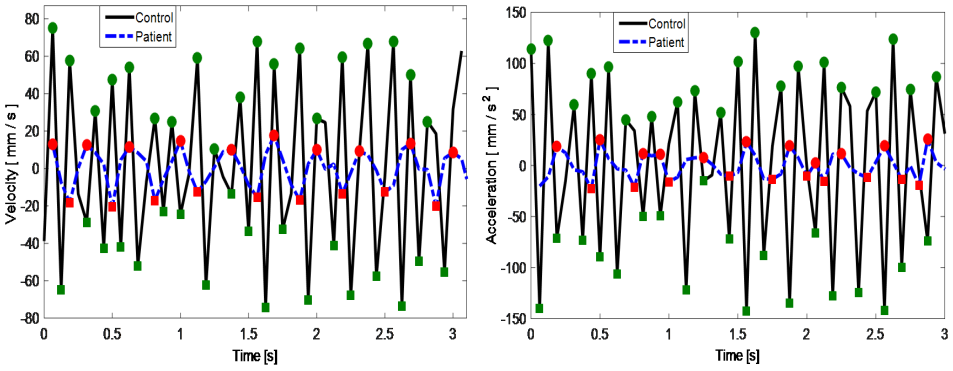


Figure 4.5: Evolution of the abduction sensor (ring-pinky position) AV data profiles during FECM

surement system is composed of two accelerometers, while in [Shima et al., 2008, 2009] magnetic sensors are used. The main drawback of these systems is the analysis of one particular movement since, due to the sensor placement, only the evaluation of the FTM is feasible.

Unfortunately, the sensor glove we used does not possess sensors on the fingertips and available joint-angle data are not enough to characterize FTM. To overcome this, we developed a hand model and used the model to estimate the fingertips position information. The hand model allows us to produce estimates of different hand-related measurements (distance, velocity, acceleration), without using specific sensors (e.g. accelerometers) for that purpose. Consequently, our approach provides a comprehensive analysis of several hand movements along with FTM, without excluding significant sensor information. The Kinematic hand model with 20 degrees of freedom is fed with the joint-angle data collected by the sensor glove and real dimensions of the subject's finger sections, measured at the time of experiments. Based on this information and using direct kinematics, the positions of the fingertips can be estimated. Every finger is treated as a serial kinematic chain, which is modeled using Denavit-Hartenberg (DH) representation [Rob; Spong et al., 2006]. As a by-product, the kinematic hand model can be used to visualize the hand movements and check whether the sensor data keep track of real finger movements within the appropriate range of motion.

The analysis of the distance information between thumb and index fingertips during FTM, estimated from the hand model, did not show significant differences between patients and healthy subjects. In contrast, derivatives of the distance signals (velocity and Accelerometer (ACC) information) illustrated large differences between patients and controls, when observing the extreme signal values (green circles and squares-control, red circles and squares-patient) during the movement sequence (Figure 4.6). Those peak values in velocity and ACC signals represent the MPIs for the FTM.



(a) (b)

Figure 4.6: Estimated velocity (a) and acceleration (b) signals from the hand model

4.4 Results

We have defined a set of 15 MPIs to characterize the hand movements. Those MPIs can be used both for diagnosis and progress monitoring of PD during rehabilitation. The design of these MPIs was grounded on the information provided by neurologists and therapists with the goal of delivering quantitative information about subject's performance. In this section, it will be shown how these MPIs can be successfully used in practice. When dealing with the proposed MPIs set, five important questions are imposed: (1) What is the internal consistency of the sensor measurements and reliability of the extracted MPIs? (2) What is the relationship between the proposed MPIs and the demographic and clinical characteristics of subjects? (3) Which MPIs are the more relevant and informative? (4) Can we improve classification results if we design an optimized MPIs set? (5) Are the proposed MPIs correlated with clinical tests and scales? To answer the first two questions we conducted statistical analysis and employed mixed effect models. To investigate questions 3-4 we adopted a Linear Discriminant Analysis (LDA) approach [Fisher, 1936]. Finally, to address the last question, we have performed correlation analysis.

4.4.1 Internal consistency of the sensor measurements and reliability of the extracted MPIs

Internal consistency of the sensor measurements is assessed using Cronbach's alpha parameter [Field, 2009]. Cronbach's alpha parameter was determined for four collected hand movements (Figures 4.2(a), 4.2(b), 4.2(c) and 4.2(d)) and eighteen sensors placed inside the CyberGlove (Figure 4.2(e)). The data set consists of patients with repeated measurements (eight patients in total). Our results across different movements and sensor outputs report the values of the Cronbach's alpha parameter within the range $[0.86 - 0.99]$, and thus confirm the high consistency of the data glove sensor

measurements.

In order to test the reliability of the extracted MPIs, the split-half method for reliability analysis [Field, 2009] has been applied. This method is explained in detail in the Section 3.5.1. Reliability of the extracted MPIs from the data glove data is assesed using Intraclass correlation coefficient (ICC) [Field, 2009]. Results are shown in the Table 4.4, along with the CIs.

Table 4.4: ICC reliability parameters for Data glove MPIs

Data glove MPIs	**ICC**	**CI**
1.	0.9745	[0.9691 – 0.9790]
2.	0.9690	[0.9624 – 0.9745]
3.	0.9765	[0.9714 – 0.9806]
4.	0.9748	[0.9694 – 0.9792]
5.	0.9854	[0.9823 – 0.9880]
6.	0.9864	[0.9836 – 0.9888]
7.	0.9865	[0.9836 – 0.9888]
8.	0.9764	[0.9714 – 0.9806]
9.	0.9029	[0.8821 – 0.9200]
10.	0.9158	[0.8977 – 0.9306]
11.	0.9205	[0.9035 – 0.9345]
12.	0.9034	[0.8827 – 0.9204]
13.	0.9703	[0.9639 – 0.9755]
14.	0.9978	[0.9973 – 0.9982]
15.	0.9988	[0.9985 – 0.9990]

Results of the reliability analysis have demonstrated high reliability of the data glove MPIs (ICC>0.90 for all MPIs). For the association between MPI numbers from Table 4.4 and corresponding MPIs please refer to Figure 4.7.

4.4.2 Statistical evaluation of the MPIs across demographic and clinical parameters

We investigated the relationship between the proposed MPIs and the demographic and clinical characteristics of subjects - age, gender, and clinical group: (i) patients/controls and (ii) disease stage group. In order to reveal whether those characteristics are statistically significantly correlated with the initially proposed MPIs, we have used mixed effect models [52]. Our initial MPIs set consisted of 19 hand movement MPIs.
Every MPI was modeled based on fixed and random effects. As fixed effects, we included the age, gender, and group effect. Intra-individual variations in repeated measures were modeled as the random effect. Statistical significance of the fixed effects was assessed by corresponding p-values (5% confidence level) after correction using Benjamini-Hochberg procedure for multiple testing. Mixed effect model fitting was performed for 19 initially proposed MPIs. The key results of the statistical analysis

lead to two main conclusions: (i) the demographic parameters, age, and gender, did not have significant influence (p>>0.05) on the MPIs and (ii) in addition, four out of 19 MPIs had no significant correlation with the clinical group effect (p>0.05). Those MPIs represent four hand movement MPIs (ROM of thumb metacarpal joint, ROM of pinky proximal joint, ROM of wrist pitch and distance parameter of the hand model). Hence, as suggested by these statistical studies, the subsequent data analysis (dimensionality reduction, classification, and correlation analysis) was carried out with the clinical group information only (demographic parameters were not relevant) and using the identified 15 ROM. Such outcomes lead to the simplification in terms of the number of clusters and data needs and rejection of four ROM in the subsequent data analysis.

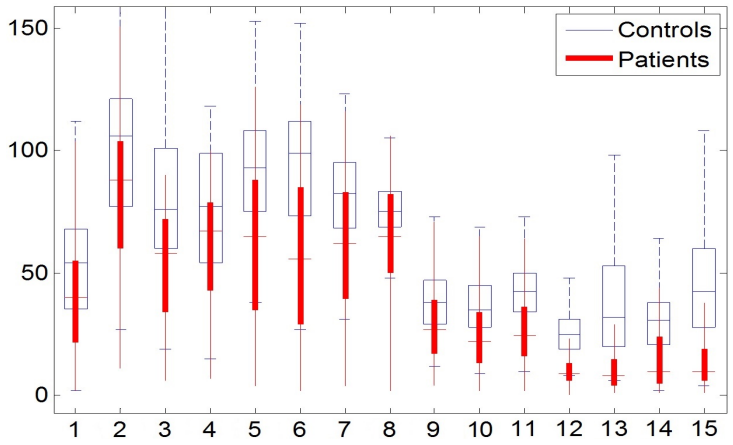


Figure 4.7: MPI ranges (sensor glove data)

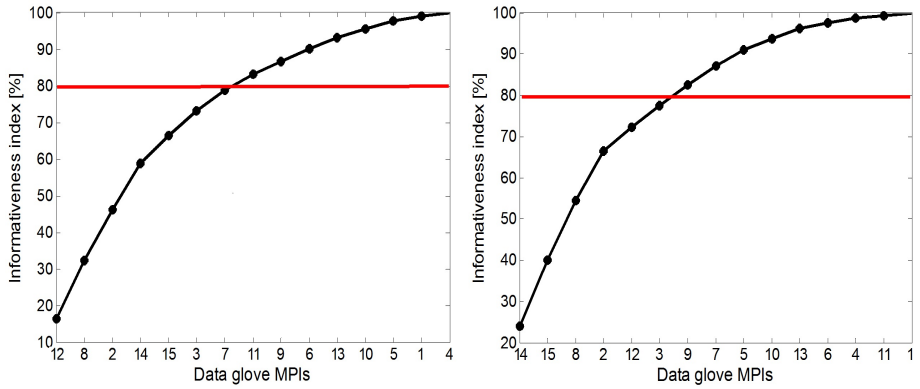
1. ROM thumb proximal [°]
2. ROM index proximal [°]
3. ROM middle proximal [°]
4. ROM ring proximal [°]
5. ROM index metacarpal [°]
6. ROM middle metacarpal [°]
7. ROM ring metacarpal [°]
8. ROM pinky metacarpal [°]
9. AVs index-middle adduction $[°/s]$
10. AVs middle-ring adduction $[°/s]$
11. AVs ring-pinky adduction $[°/s]$
12. AVs thumb-index adduction $[°/s]$
13. ROM wrist yaw [°]
14. Velocity hand model $[mm/s]$
15. ACC hand model $[mm/s^2]$

Figure 4.7 provides the insight into hand movement MPIs across patients and controls. It illustrates lower values of finger joints Range of Motion (ROM) in the patient group, as expected (Figure 4.7, 1-8 and 13). Our experiments have shown especially large differences in Angular velocity (AV) values between patients and controls for Fingers expansion and contraction movement (FECM) (Figure 4.7, 9-12), as well as in the case of MPIs extracted from the hand model (Figure 4.7, 14-15). Hence, the results confirm that our newly proposed MPIs would give significant contribution to support the evaluations in PD.

4.4.3 Dimensionality reduction

By adopting the proposed MPIs for the tested hand exercises, we obtain a set of 15-dimensional vectors (Figure 4.7), which can be used in a classification system to assist diagnosis and monitoring. We applied Linear Discriminant Analysis (LDA) [Fisher, 1936] to transform the original data sets into a new, compact, lower dimensional space, and to determine the reduced set containing the most relevant MPIs for the decision-making process (diagnosis and monitoring support). The LDA approach is explained in detail in the Section 3.5.2. Since the LDA approach aims to maximize the between-class distance and to minimize the within-class dissipation, the reduced set is formed from the most relevant MPIs according to the classification tasks. We address both classification tasks of interest (patients vs controls and disease stages). The criterion of capturing 80% of the information from the original data sets is applied. For this purpose, information index defined in the Section 3.5.2 was used (Eq. 3.12).

Consequently, we have chosen first seven MPIs during LDA analysis for groups of patients and controls and six MPIs from the LDA procedure in the case of disease stages (Figure 4.8). MPIs 12, 8, 2, 14, 15, 3 and 7 from Figure 4.7 have the highest contribution to differentiate classes of patients and healthy-subjects, while MPIs 14, 15, 8, 2, 12 and 3 were the most representative MPIs during dimensionality reduction according to disease stage classes. This result suggests that the MPIs extracted from the hand model are the most relevant MPIs in both cases. In addition, ROM MPIs (FFEM – both proximal and metacarpal joints) and angular velocity MPIs (FECM – thumb-index abduction sensor), are also very important in the data analysis.

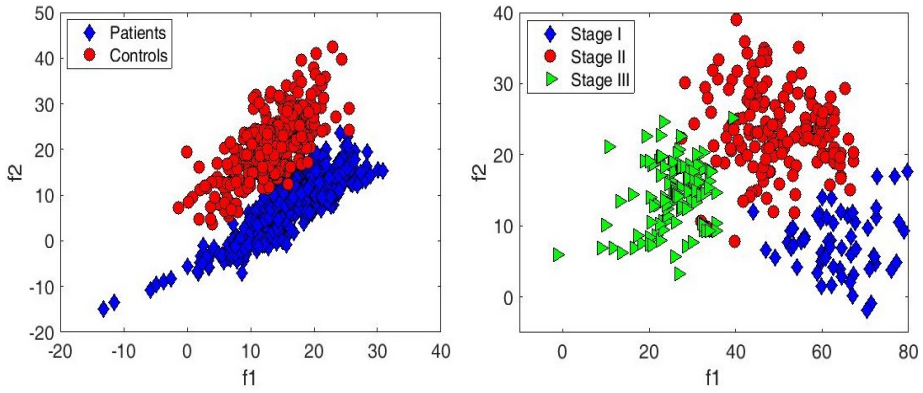


(a) (b)

Figure 4.8: LDA Informativeness index: (a) patients-controls and (b) disease stages data.

The dimension of the newly created space is determined from the eigenvalues of the LDA criterion function, which takes into account the class covariances. Our tests revealed that the sum of the first two eigenvalues was much larger than the sum of the

remaining eigenvalues ($\lambda_1 + \lambda_2 \gg \lambda_3 + \cdots + \lambda_m$), where m is the total number of MPIs. Hence, we reduced the original MPI set to the new 2-dimensional feature space.



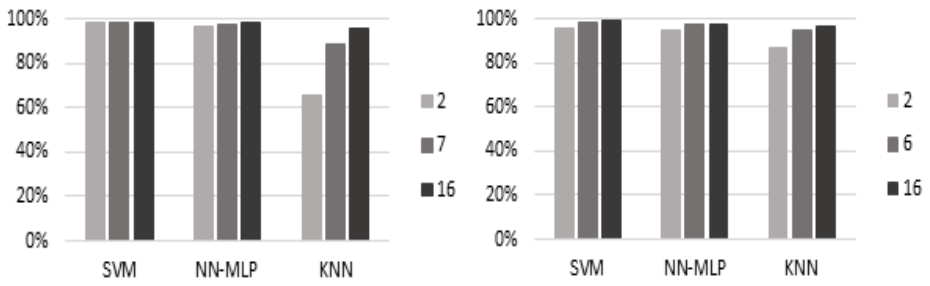
(a) (b)

Figure 4.9: Synthetic features can successfully differentiate the different groups of subjects and conditions: (a) patients-controls and (b) disease stages

While these new synthetic features have the power to differentiate the different conditions in the data (Figure 4.9), they are less efficient in terms of communication and understanding for the medical doctors and therapists, as they do not correspond to a specific MPI.

4.4.4 Classification: diagnosis and monitoring evaluations

The classification process for sensor glove data was performed between the groups of controls and patients (support for diagnosis) and between patients with different disease stage (support for monitoring). Three different classifiers are tested with the original MPI set, six/seven most relevant MPIs and two new synthetic features obtained from LDA (Figure 4.10). SVM are designed with the RBF kernel, whereby the bandwidth of the RBF kernel, σ varies between 0.01 and 1 and regularization parameter, C varies within a range [0.01 – 10]. KNN classifier is tested for the $k = 1, 3$ and 5 nearest neighbors. The neural networks classifier is a MLP with a different number of hidden layers and nodes. The parameters of classifiers are chosen from listed ranges in a validation procedure in order to achieve the highest accuracy rate. The best results on the testing set for all classifiers are obtained with the original 15D feature set. The classification accuracy is above 90% for the six/seven most relevant feature set. The lowest classification rates are reported in the case of new reduced feature space, due to the significant information losses during dimensionality reduction procedure. These results confirm the higher informativeness of the sensor glove MPIs compared to the Kinect data MPIs and their ability to participate in both, diagnosis and monitoring evaluations of PD. Such outcome is expected, due to the high importance of hand movement analysis and quantification for PD assessment.



(a) (b)

Figure 4.10: Classification accuracy sensor glove data: (a) patients / controls and (b) disease stages

4.4.5 Correlations with clinical scales

We have confirmed the potential of the chosen MPIs to support the decision-making systems for diagnosis and monitoring evaluations. Another important issue is to investigate the correlation between the proposed MPIs and clinical test and scales. This is particularly important for the possible inclusion of the proposed MPIs into rehabilitation protocols. The correlation analysis is carried out between the proposed hand MPIs (Figure 4.7) and tapping test [Potter-Nerger et al., 2009] and UPDRS-III clinical scale [Goetz et al., 2008]. The tapping test is performed by patients while UPDRS-III values result from the neurologist's evaluation. Correlations were calculated using Pearson's correlation coefficient r (takes values between -1 and 0 for negative correlation and between 0 and 1 for positive correlation), along with the p-value (testing the hypothesis if two variables are correlated). Scatter plots in Figure 4.11 illustrate the correlation between selected MPIs and clinical parameters, where the line represents the regression curve. It can be seen that the selected MPIs have a positive correlation with the tapping test, more concretely with the number of taps performed by the subject's right-hand palm (procedure of the tapping test is previously explained in the Section 4.2.2). This is expected since the patients who have higher values of ROM and ACC parameter potentially can achieve a larger number of taps within defined period (30 seconds). On the other side, our MPIs have a negative correlation with the UPDRS-III scale, since the lower values of our MPIs and higher values on this scale indicate a more severe state of the patient i.e. higher disease stage.

Results of the correlation analysis (Table 4.5) have shown that some MPIs are highly correlated with both clinical parameters such as ROM of the proximal finger joints (1-4) and velocity and ACC parameters derived from the hand model (14, 15). ROM of the metacarpal finger joints (5-8) have shown good correlation with the tapping test, but not very high correlation with UPDRS-III scale. AV MPIs extracted from the abduction sensor data (9-12) and ROM of wrist yaw (13) are poorly correlated with both clinical parameters, except correlation of MPIs 9 and 11 with tapping test.

Table 4.5: Correlation between the data glove MPIs and tapping test / UPDRS-III clinical scale

	Correlation coefficient r and p-value	
Data glove MPIs	**Tapping test**	**UPDRS-III**
1. ROM thumb proximal **2. ROM index proximal** **3. ROM middle proximal** **4. ROM ring proximal**	$r > 0.5$, $p < 0.05$	$r < -0.5$, $p < 0.05$
5. ROM index metacarpal **6. ROM middle metacarpal** **7. ROM ring metacarpal** **8. ROM pinky metacarpal**	$r > 0.5$, $p < 0.05$	$r > -0.5$, $p > 0.05$
9. AVs index-middle adduction	$r > 0.5$, $p < 0.05$	$r > -0.5$, $p > 0.05$
10. AVs middle-ring adduction	$r < 0.5$, $p > 0.05$	
11. AVs ring-pinky adduction	$r > 0.5$, $p < 0.05$	
12. AVs thumb-index adduction **13. ROM wrist yaw**	$r < 0.5$, $p > 0.05$	
14. Velocity hand model **15. ACC hand model**	$r > 0.5$, $p < 0.05$	$r < -0.5$, $p < 0.05$

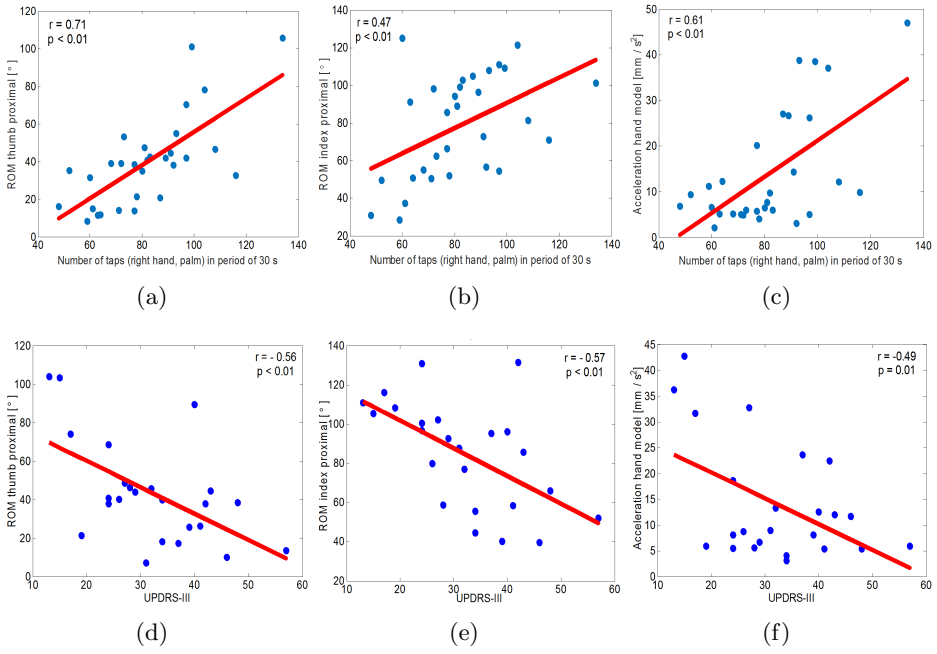


Figure 4.11: Scatter plots of the correlation between particular MPIs and (a-c) tapping test and UPDRS-III scale (d-f)

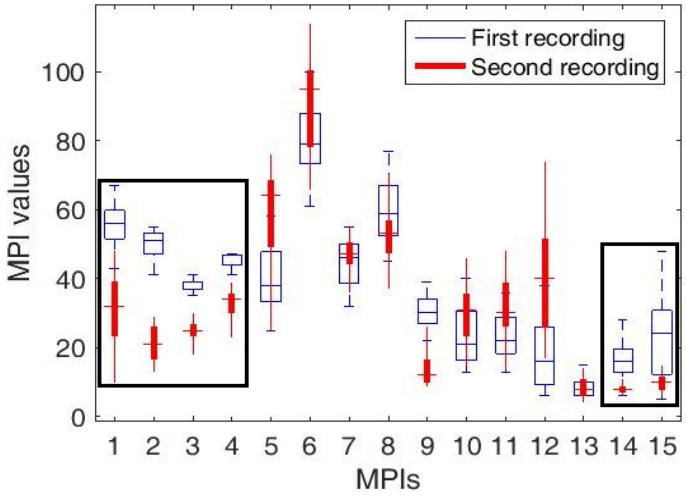
4.5 Repeated experiments with data glove

In order to investigate whether our proposed hand MPIs can keep track of the patients' performance over time in the same way as clinical measurements, we have conducted the repeated experiments of the tested hand movements. In PD, the patients' condition in the sense of movement performance changes very slow and the period between significant changes is usually at least one to two years. The most common outcome is the decreasing of the movement performance with the time.
However, even if the disease has a progressive character, some patients experience improvements in movement performance over time. Such result can be a consequence of the following factors: (i) patient's initial state was bad and it is improved later with the therapy. Drug treatment keeps the disease under control leading in addition to better condition. (ii) Drug treatment changes. Drug treatment in PD is individual and finding the right drug combination is still a big challenge in PD. Consequently, during the disease progress, the patient can receive more appropriate therapy than the initial one.

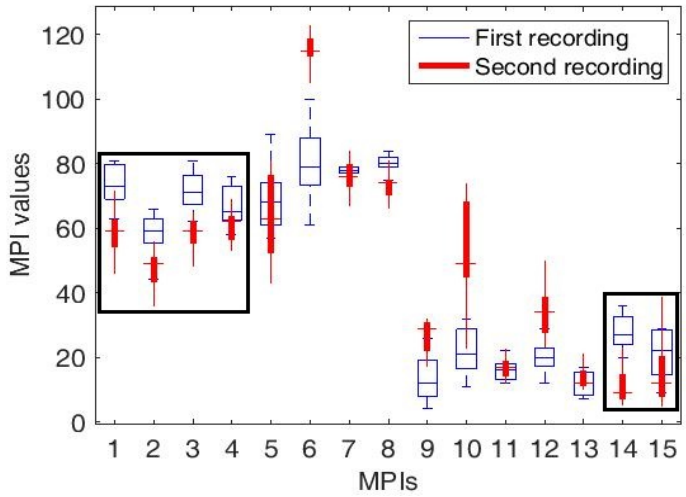
Table 4.6: Clinical scale measurements for the first and second (repeated) recording

	First recording		**Second recording**	
Patients	**HY**	**UPDRS-III**	**HY**	**UPDRS-III**
Patient 1	2	26	3	34
Patient 2	2	24	3	33
Patient 3	1	19	1	15

Figure 4.12 illustrates the MPI values for the first and second (repeated) recording, while the Table 4.6 gives the insight about clinical scale measurements collected at the same time as sensor measurements. The assosiation of the MPI number (1-15) on x-axis with the corresponding MPI can be found in the Table 4.5. The results for Patient 1 and Patient 2 report decrease in the movement performance according to the clinical scales, since higher values of clinical scales indicate more severe state (Table 4.6). However, only particular MPIs confirm clinical results. Those MPIs are labeled with black rectangle in Figure 4.12 and correspond to the ROM of the proximal finger joints (1-4) and velocity and ACC parameters derived from the hand model (14, 15) - Table 4.5. Table 4.5 underlines that those MPIs are also correlated with both, clinical tapping test and UPDRS-III scale. Consequently, the results of the repeated measurement analysis are in accordance with the correlation with clinical test and scale analysis, explained in the previous Section 4.4.5. The same conclusion is applicable for to Patient 3, with the exception that her performance improved over time. Patient 1 is recorded again after 13 months, Patient 2 after 30 months and Patient 3 after 23 months.



(a)



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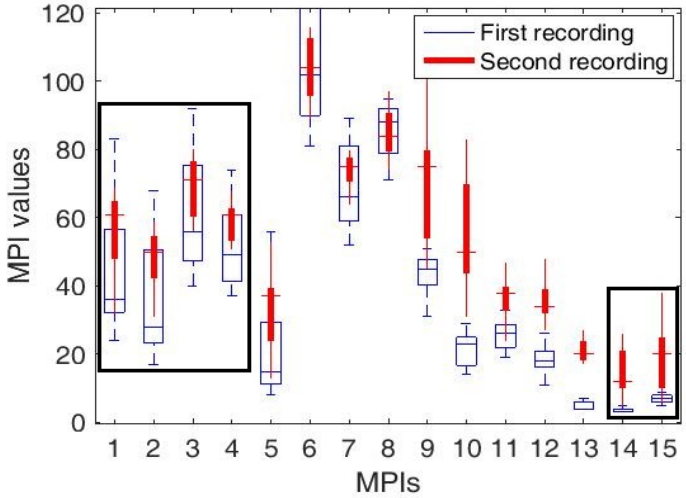


(c)

Figure 4.12: Repeated experiments of the tested hand movements in the context of the proposed MPIs: (a) Patient 1, (b) Patient 2 and (c) Patient 3

4.6 Summary and discussion

An approach for quantitative movement analysis to support and advance traditional clinical techniques is presented, based on the hand movement data. The results suggest that the proposed approach could be adopted by therapists, to enhance objectivity and precision, during the diagnosis and monitoring evaluations. At the same time, it can improve a patient's motivation for the therapy (bringing the innovations in the standard rehabilitation protocols with new-sensing technologies) and offer the possibility of home rehabilitation for patients from the mild to moderate PD stages (I-III according to the modified HY clinical scale). The final goal is to develop a low-cost and portable sensor system for comprehensive movement analysis, suitable for home rehabilitation. The data glove device has been used as the proof of concept for the hand movement analysis, but due to its high cost, the final version of the system, will contain alternative low-cost data glove. A set of 15 MPIs is proposed to characterize the hand movements of subjects, based on the sensor data, in the context of PD. We conducted a thorough analysis of the properties of these MPIs, to identify the most informative in terms of assisting both the medical diagnosis and progress monitoring. This process unveiled the significant role of the new MPIs we proposed: angular velocity MPIs extracted from the abduction sensor data and velocity and acceleration MPIs derived from the hand model, accompanying with the finger joint's range of motion. On the other hand, correlation analysis showed that the ROM of the proximal finger joints and velocity and acceleration parameters are strongly correlated with clinical scales. Consequently, these MPIs satisfy both important conditions for inclusion in the rehabilitation protocols – high relevance for the PD symptom assessment and important role in diagnosis and monitoring evaluations through decision-making systems.
The MPIs obtained from the Kinect and data glove data were analyzed separately and can be used in different ways. The full-body MPIs are suitable to be used by therapists as a first step for the preliminary assessment of the subject's condition (detecting motor disorders). In a second step, more detailed analysis can be performed to determine the disorder severity (disease stage) using hand movements MPIs. The results have shown significant differences between patients and controls for the all proposed MPIs and the possibility of successfully classifying the two conditions. The data glove sensor has proven to be more informative than the Kinect for assessing the PD main symptoms and the disease stages. This is due to the higher importance of the fine hand movement analysis, particularly for PD evaluations in comparison to the full-body movements.

Chapter 5

Quantitative assessment of the arm / hand movements in Parkinson's disease using wireless armband device

In the previous chapters we have dealt with vision-based sensor (Kinect device) to quantify full-body movements (gait and large-range upper body movements) and sensor glove (CyberGlove II device) to quantify hand movements of Parkinson's patients. We proposed novel scores called Movement Performance Indicator (MPI), that are extracted directly from the sensor data and quantify the symmetry, velocity, and acceleration of the movement of different body/hand parts. Our approach for the hand movement characterization, based on the sensor glove data, has demonstrated significant results and ability to support the diagnosis and monitoring evaluations in PD (Chapter 4). Still, due to the high cost, it does not fit into our concept of a low-cost rehabilitation system for movement analysis. Another limitation arises from the right-hand design of the sensor glove device. This implies that only right-hand movements can be tested and hence, only right side affected patients are taken into account. Consequently, left-right side analysis as an important indicator of the disease progression, cannot be conducted. In this chapter, we focus on quantification of the arm/hand movements from measurements acquired with the wireless wearable armband device - Myo sensor, in order to reveal whether the armband sensor can be a suitable alternative for the sensor glove. This device is placed on the forearm and outputs Electromyography (EMG) data from eight channels. Electromyography (EMG) data give insight into the muscle activity information. Impaired muscle activity and restriction of motor functions are common characteristics of PD. The armband device contains also 3-axis accelerometer and 3-axis gyroscope, which output acceleration and angular velocity

information, respectively. Here, we present extensive experiments and analysis conducted to address the following aspects: (i) quantitative evaluation of the arm/hand movements of Parkinson's patients, (ii) inspection of bradykinesia motor symptom, (iii) assessment of the performance differences between left and right arm/hand movements and (iv) investigation whether the armband sensor can be an adequate low-cost alternative for the sensor, due to its high cost. Aspects addressed in (i)-(iii) are worth to be investigated in the treatment of Parkinson's disease, but their direct assessment is not possible considering the limited resources and standard techniques used by doctors.

5.1 Proposed system structure

The proposed system structure for quantitative assessment of the arm/hand movements using the Myo armband device is illustrated in Figure 5.1.

Myo armband is wearable and wireless device that is placed on the forearm. It outputs Electromyography (EMG) data from eight channels (sampling rate 200 Hz). EMG data give insight into the muscle activity information. The armband device contains also 3-axis accelerometer and 3-axis gyroscope, which output acceleration and angular velocity information, respectively (also called Inertial measurement unit (IMU) data, collected with sampling rate 50 Hz).

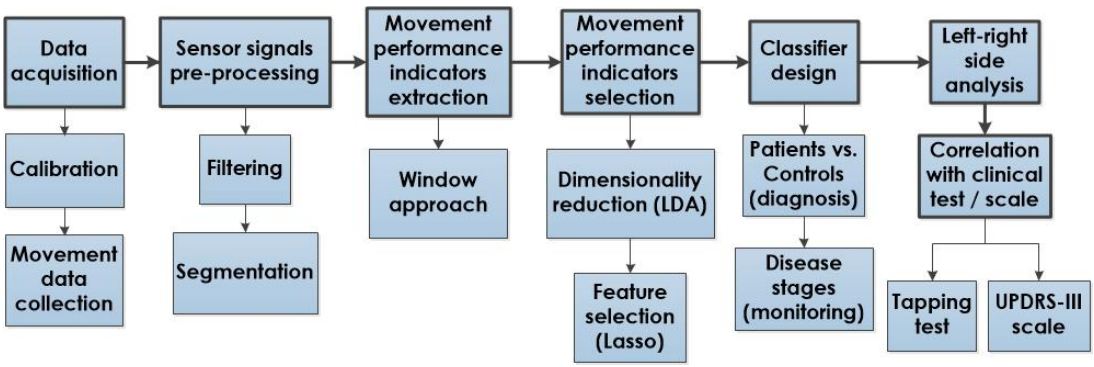


Figure 5.1: Proposed system structure

The armband device needs to be synchronized, using particular arm-hand movement, before the data collection. As a second stage, the sensor signals are pre-processed with low-pass filters to reduce the measurement noise. The MPIs are extracted from all consecutive movements in one sequence at the same time. Hence, the segmentation procedure is performed only to remove the non-informative signal parts at the beginning and at the end of the sensor signals. For characterizing the arm/hand movements i.e. MPI design, the window-based approach has been adopted (Section 5.3). All proposed MPIs are further tested in terms of the following clinically relevant aspects: (i) reliability; (ii) ability to discriminate between the patients and controls, and between the disease stages (support to disease diagnosis and progress monitoring,

respectively), Section 5.4.2; (iii) performance analysis and comparison between the left-hand and the right-hand movements across controls and patients, as well as across disease stage groups (Section 5.4.3) and (iv) correlation with clinical scales (tapping test and UPDRS-III Motor Score), Section 5.4.4.

5.2 Experimental procedure

5.2.1 Participants

The experimental group consists of seventeen PD patients with personal and disease characteristics listed in Table 5.1. Similar like in the case of the full body and hand movements, we focus on the PD patients from I to III disease stage according to modified HY scale. A control group is formed by sixteen age-matched volunteers without any history of neurological or movement disorder. All subjects have been examined under the same conditions and they have performed four hand movements, instructed by a neurologist and therapists. The experimental protocol, designed by the movement disorder specialists (Table 5.2, Fig. 5.2) includes six exercises performed with the left and right hand: four arm/hand movements and two tapping test movements, well-established experimental paradigm designed for bradykinesia assessment ([Potter-Nerger et al., 2009]). The tested movements are chosen to closely reflect the patient's activities of daily living that engage forearm muscles. The movements have been performed with the left and right hand, respectively, and acquired using the armband sensor.

Table 5.1: Patient characteristics

Age (years), mean (SD)	63.5 (8.3)
Range	47-75
Gender (number of patients)	Males (17)
	Females (0)
Modified Hoehn and Yahr (HY) stage, mean (SD)	2.59 (0.93)
Range, 1-5	1-3
UPDRS motor score (section III), mean (SD)	31.82 (15.43)
Range, 0-108	12-67
Duration of PD (years), mean (SD)	4.7 (2.5)

5.2.2 Experimental protocol

The medical procedure adopted in PD analysis includes a set of movements/exercises, in order to allow doctors to make a qualitative evaluation of the disease stage and progress. The first two exercises emulate the bulb screwing / unscrewing in two variations: Rotation of the hand movement with elbow extended (RH-EE), Fig. 5.2a and Rotation of the hand movement with elbow flexed at 90° (RH-EF), Fig. 5.2b. Those

Table 5.2: Acquired movements according to the experimental protocol

	Acquired movements according to the experimental protocol
1.	Rotation of the hand movement with elbow extended (RH-EE)
2.	Rotation of the hand movement with elbow flexed at 90° (RH-EF)
3.	Movement of object grasping, pick and place in the case of easy load (GPP-EL)
4.	Movement of object grasping, pick and place in the case of heavy load (GPP-HL)
5.	Proximal tapping task (TT-P)
6.	Distal tapping task (TT-D)

movements were acquired during the period of 10 seconds. The following two exercises relate to the Movement of object grasping, pick and place in the case of easy load (GPP-EL), Fig. 5.2c and Movement of object grasping, pick and place in the case of heavy load (GPP-HL), Fig. 5.2d. Those movements were repeated five times. The last two exercises represent the tapping test. The test consists of the proximal and distal tapping tasks using a specially designed board as the one proposed in (Potter-Nerger et al. [2009]). Proximal tapping task (TT-P) refers to the alternate pressing of two large buttons located 20 cm apart with the palm of the hand, during the 30 seconds interval (Fig. 5.2e). Distal tapping task (TT-D) is related to the alternate pressing of two closely located buttons (3 cm apart) with the index finger while the wrist is fixed on the table during 30 seconds (Fig. 5.2f). The acquired data consist of: (i) EMG data from 8 channels (sensor data rate 200 Hz) and (ii) 3-axes IMU data - acceleration and angular velocity (sensor data rate 50 Hz).

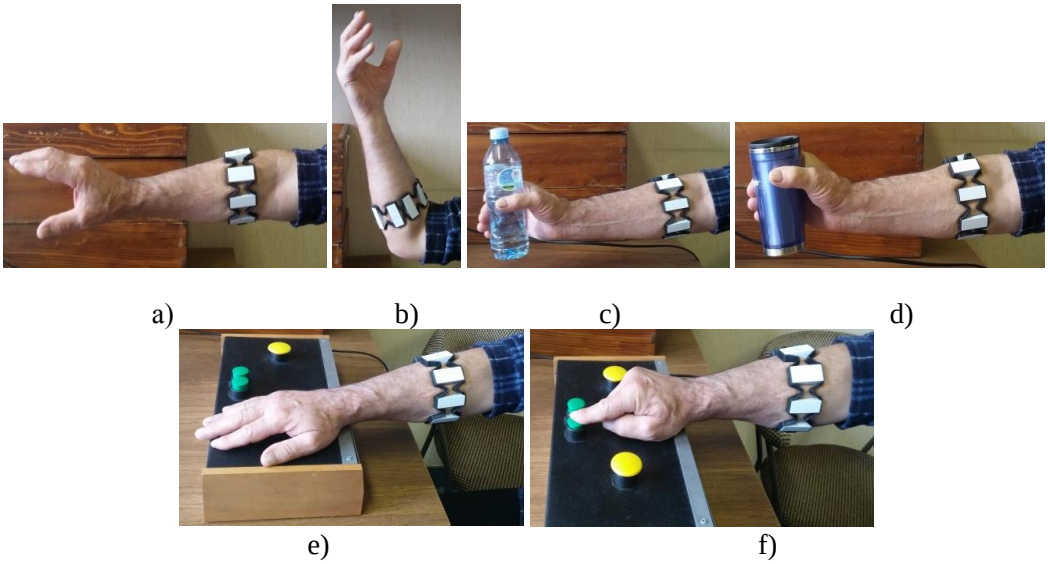


Figure 5.2: Acquired movements according to the experimental protocol: RH-EE (a), RH-EF (b), GPP-EL (c), GPP-HL (d), TT-P (e) and TT-D (f)

The clinical measurements (HY and UPDRS) are collected by one experienced rater immediately before the sensor measurements. All measurements have been performed in the hospital settings for outpatients. The clinician was present during the sensor measurements in order to monitor the patient state, and to prevent situations in which the patient is quickly switched from ON (the effect of medication present) to OFF state (the effect of medication stopped), due to which the possible clinical measurement and sensor measurement would be carried out under different conditions. The HY clinical values (which evaluate the disease stage) were assessed using the modified Hoehn and Yahr (HY) Scale [Goetz et al., 2004]. The UPDRS clinical values (which evaluate the motor symptoms) were assessed using the motor part of the Unified Parkinson's Disease Rating Scale (UPDRS) [Goetz et al., 2008].

Figure 5.3: Board for tapping test

5.3 An approach to movement characterization

In this section, we explain the design of the seven basic measurements, based on which MPIs are grounded. The choice of the basic measurements is based on the properties of the sensor signals in the time domain (signal amplitude). Such choice is a consequence of the statistically significant differences in the amplitude of signals collected from patients and controls. The readings from the EMG electrodes, as well as outputs from an accelerometer and gyroscope, are used for movement characterization.

Since the EMG signals are highly non-stationary, the most common approach for the processing of the EMG signals is the window approach (Phinyomark et al. [2009]; Boostani and Moradi [2003]). This method implies the temporal segmentation of the signal into sliding windows and calculating the particular value of basic measurements for each separate window (Figure 5.4). The same technique has been applied to the signals obtained from the accelerometer and gyroscope. The main benefit of the window analysis is to characterize the temporal evolution of basic measurements during the movement.

The common choice of the window length is one to three times of the fundamental signal period (Rabiner and Gold [1975]). Accordingly, we set the window length to

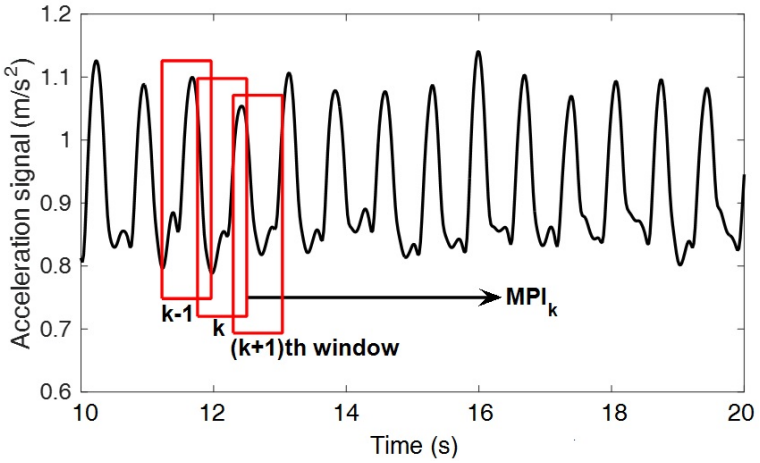


Figure 5.4: Window approach for basic measurements extraction illustrated for the case of the acceleration signal

200 ms for EMG signals and 800 ms for signals from accelerometer and gyroscope. The length of the overlapping segment usually amounts 25-50% of the window length as suggested in (Phinyomark et al. [2009]; Boostani and Moradi [2003]). We choose the length of the overlapping segment as 25% of the window size, hence 50 ms for EMG signals and 200 ms for signals from accelerometer and gyroscope. We have tested different lengths of the window and overlapping segment and the results were not sensitive to those choices of the length.

Before the basic measurements calculation, the signals are pre-processed to remove the measurement noise and for performing temporal segmentation. In our experiments, all signals were filtered with Butterworth low pass filter. Cut-off frequencies and order of the filter were chosen in accordance with the signal sampling rate and the frequency characteristic of the meaningful signal content. The segmentation procedure is required in order to remove the non-informative signal parts at the beginning and at the end of the signals. For this purpose, the threshold based on the signal energy in the time domain has been adopted.

5.3.1 Quantification of the EMG signals

Various measurements have been proposed in the literature for characterization of the EMG signal (Phinyomark et al. [2009]; Boostani and Moradi [2003]; Huang et al. [2013]; Arief et al. [2015]; Phinyomark et al. [2012]). Our choice of suitable basic measurements from EMG signal relies on the signal amplitude properties; hence we tested amplitude-based measurements that are most often used in the literature. Thus, we have quantified obtained EMG signals using the Mean absolute value (MAV) (5.1), Variance (VAR) (5.2) and Waveform change (WC) (5.3). In equations (5.1)-(5.3), W_n represents the window length, expressed in signal samples.

$$Emg_{MAV} = \frac{1}{W_n} \sum_{t=1}^{W_n} |EMG(t)| \tag{5.1}$$

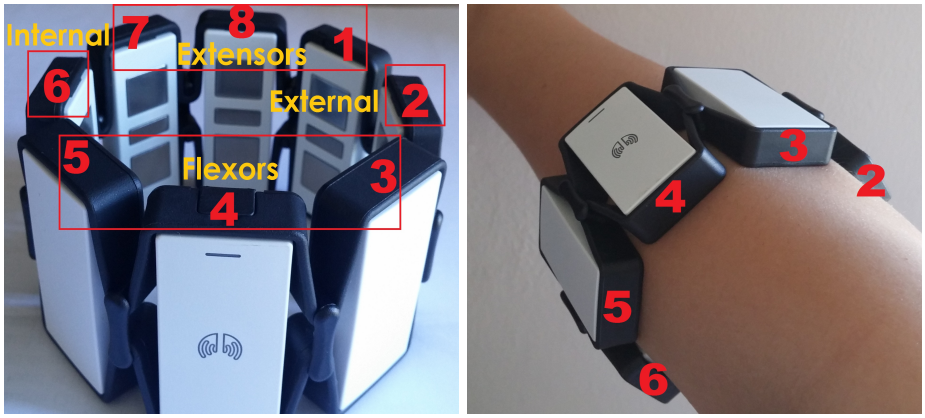
$$Emg_{VAR} = \frac{1}{W_n} \sum_{t=1}^{W_n} EMG(t)^2 \tag{5.2}$$

$$Emg_{WC} = \sum_{t=1}^{W_n - 1} |EMG(t+1) - EMG(t)| \tag{5.3}$$

The armband sensor consists of eight EMG channels labelled as shown in Figure 5.5(a). During the experiments, the sensor was placed in the same position for every subject (Figure 5.5(b), right hand). It can be seen that for the right-hand channels 3, 4 and 5 cover the upper forearm (extensors muscles), channels 7, 8 and 1 are placed on the lower forearm (flexors muscles), channel 2 covers the external forearm muscles, while the channel 6 is placed on the internal forearm muscles. As for the left hand, extensors and flexors are covered with the same groups of channels, while the channels 2 and 6 are replaced between internal (channel 2) and external (channel 6) forearm muscles.

The comparative analysis between patients and control subjects across six collected movements and eight EMG channels have been conducted in order to investigate whether the EMG data from particular channels are more discriminative than others. The amplitude of the EMG signals was used as the comparison criteria, whereby the signal amplitudes (after filtering) were particularly larger in control group than in patients. The results are indicative of significant differences in the case of the right-hand movements from the channel 2 and for the left-hand movements at the channel 6. It can be seen from the Figure 5.5, that those electrodes cover the same group of external forearm muscles in the case of both hands. The clinical evaluation of this result still needs to be investigated, but our results suggest that this particular group of muscles is the most affected by PD, since the muscle activity was the lowest of all tested forearm muscles. Hence, the extraction of basic measurements has been performed only for the signals from channel 2 for the right-hand movements and from channel 6 for the left-hand movements.

Figure 5.6(a) shows the mean absolute value and the standard deviation graph of the extracted EMG basic measurements (5.1), (5.2) and (5.3) for groups of patients and controls. Presented basic measurements are extracted from the movement of object grasping, pick and place - heavy load, performed with the right hand (GPP-HL, Figure 5.2d). It can be seen that the values of basic measurements are larger in the controls than in patients, especially in the case of VAR feature. Figure 5.6(b) shows the temporal evolution of the Mean absolute value from EMG signal (EMG-MAV) over window segments, for patients and controls, during the GPP-HL movement. This



(a) (b)

Figure 5.5: Labeled channels of the armband sensor (a) and armband sensor placement on the right hand during experiments (b)

movement was repeated five consecutive times during the experiment. It can be seen that the patients have performed slower movements (number of windows is larger in the case of patients, since the signals are longer in time). Such outcome clearly illustrates the bradykinesia symptom at patients.

5.3.2 Quantification of the signals from an accelerometer and gyroscope

The accelerometer (ACC) and gyroscope (GYRO) signals are quantified using the same time-window approach as for EMG signals. The choice of basic measurements is different, in accordance with the signal characteristics and the properties of its transformations (such as signal derivative). The accelerometer and gyroscope signals are not processed in their original form. Instead, the basic measurements are extracted from their time-derivatives. A comparative analysis between patients and controls, for accelerometer and gyroscope signals, shows that the signal derivative enlarges the differences between the groups of interest.

Since both the accelerometer and gyroscope have three axes, depending on the particular movement, the data from one axis are more relevant than the data from the remaining two. Consequently, for each movement, corresponding axis of interest is adopted. Extracted basic measurements are Simple square integral (SSI) and Range (RAN), given by the equations (5.4) and (5.5), respectively, where $\dot{x}(t)$ represents the accelerometer or gyroscope signal derivative.

$$(Acc/Gyro)_{SSI} = \sum_{t=1}^{W_n} \dot{x}(t)^2 \tag{5.4}$$

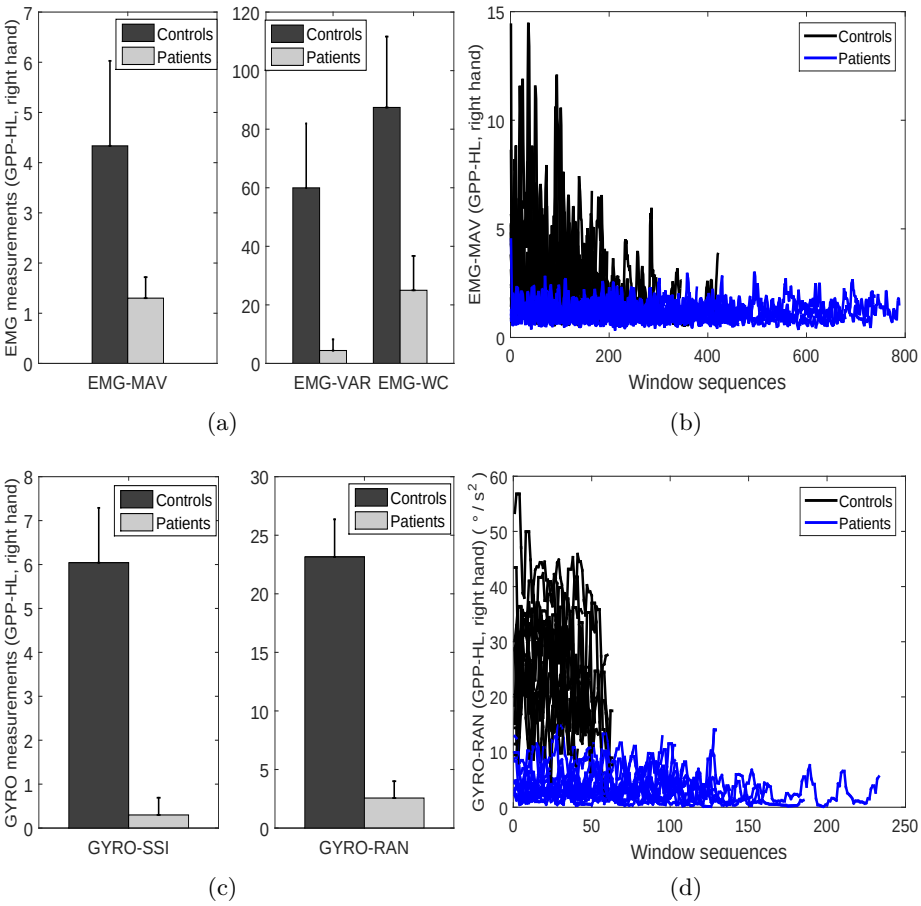


Figure 5.6: Extracted basic measurements across groups of interest: (a) EMG basic measurements; (b) Temporal evolution of EMG-MAV over window segments; (c) GYRO basic measurements and (d) Temporal evolution of GYRO-RAN over window segments * y-axes are labelled in the form: basic measurement(s) (performed movement, hand)

$$(Acc/Gyro)_{RAN} = max(\dot{x}(t)) - min(\dot{x}(t)), \quad t \in \{1, W_n\} \tag{5.5}$$

The above specified basic measurements are directly related to the signal amplitude - larger amplitude indicate larger value of basic measurements defined by (5.4) and (5.5). Figure 5.6(c) shows the mean absolute value and the standard deviation graph of the extracted GYRO basic measurements (5.4 and 5.5) for groups of patients and controls. Illustrated basic measurements are extracted from the Movement of object grasping, pick and place in the case of heavy load (GPP-HL) (Figure 5.2d). It can be seen that the values of basic measurements are larger in the controls than in the patients, which is an expected result. Additionally, since the GPP-HL movement (Fig. 5.6(d)) was repeated five times consecutively during the experiment, controls performed those movements faster than patients (number of windows is lower in the case of controls, since the signals are shorter in time). Such result is the direct consequence

of the bradykinesia symptom in patients, since they demonstrated significantly slower movements than controls.

5.3.3 Summary and reliability of the basic measurements

In total, we have extracted seven basic measurements (Table 5.3) for each movement. We characterize twelve movements - six different movements (Table 5.3, Fig. 5.2) were performed by both left and right hand. Consequently, based on the seven basic measurements calculated for each movement, we obtained a total set of 84 MPIs for all movements (seven basic measurements times twelve movements). In the following section, we will reveal which MPIs are the most relevant and informative, from the view of particular clinical aspects.

Table 5.3: Calculated basic measurements

	Calculated basic measurements
1.	Mean absolute value from EMG signal (EMG-MAV)
2.	Variance from EMG signal (EMG-VAR)
3.	Waveform change from EMG signal (EMG-WC)
4.	Simple square integral from accelerometer signal derivative (ACC-SSI)
5.	Range from accelerometer signal derivative (ACC-RAN)
6.	Simple square integral from gyroscope signal derivative (GYRO-SSI)
7.	Range from gyroscope signal derivative (GYRO-RAN)

In order to test the reliability of the extracted MPIs, the split-half method for reliability analysis (Field [2009]) has been applied. The split-half method divides the conducted tests into two parts and correlates the scores on one-half of the test with scores on the other half of the test. Thus, the split-half method estimates the reliability based on the repetitions inside the same trial. Reliability of the extracted MPIs is assessed using Intraclass correlation coefficient (ICC) (Field [2009]). ICC has a value inside range [0 - 1], whereby the values closer to 1 indicate higher reliability.

Our initial set of basic measurements consisted of ten different measurements. In addition to the previously described seven basic measurements, three more measurements were calculated in the frequency domain representing the signal energy characteristics. However, the results of the reliability analysis have shown the poor reliability of the frequency domain measurements (ICC < 0.50). Hence, they are excluded from the further analysis. Other seven basic measurements demonstrated high reliability, with ICC values greater than 0.90.

5.4 Results

5.4.1 Dimensionality reduction and MPIs selection

Finding lower-dimensional representations which still preserve the most relevant information contained in the original data is key for many machine learning and data mining applications. It results in reduced data needs, reduced computational cost for algorithms, and often even increases the predictive performance of the learned models. Also, data visualization is much easier in low dimensions, and can lead to important insights regarding the process of interest. Therefore, we have used two popular approaches for dimensionality reduction and feature selection, LDA (Fisher [1936]) and Least Absolute Selection Shrinkage Operator (LASSO) regression (Tibshirani [1996]), to find most relevant MPIs. LDA is a dimensionality reduction approach which finds the most discriminative principal components (linear combination of features), but can also rank the features by their importance. LASSO regression performs feature selection by assigning zero weights to less relevant features, giving them zero influence on the targeted outcome. Theoretically, the LASSO regression is more adequate to non-Gaussian type of data than LDA, but in practice they have similar predictive performance. Both algorithms have the same computational complexity, cubic in the number of features ($O(k^3)$) and linear in the number of examples ($O(k^2 * n)$), where k is the number of features and n is the number of examples.

We applied Linear Discriminant Analysis LDA (Fisher [1936]) to determine the most relevant MPIs for the decision-making process based on the clinical group parameter, between patients and controls (diagnosis support) and between disease stages (monitoring support). Another outcome of the LDA algorithm is the transformation of the MPI dataset into a new, compact, lower dimensional space. The LDA approach aims to maximize the between-class distance and to minimize within-class dissipation. Implementation of the LDA method is based on the procedure described in detail in Section 3.5.2. Information index (Eq. 3.12, Section 3.5.2) plots (Figures 5.7(a) and 5.7(b)) show the importance of the MPIs for classification tasks from the ones most important towards less important MPIs. The LDA method results that, for keeping 80% of information from the original data set, it is sufficient to select first 13 out of 84 MPIs for both conditions: patients/controls (Figure 5.7(a)) and disease stages (Figure 5.7(b)). The selected MPIs are listed in the Table 5.4. Information index plots also demonstrate that some MPI have the negligible impact on the classification tasks. After the first 50 MPIs, adding more MPIs will not bring significant information.

In order to verify the results obtained by LDA, we have used the LASSO regression analysis (Tibshirani [1996]), which performs both feature selection and regularization, in order to enhance the classification accuracy. Using the LASSO regression, the response variable (corresponding class of the interest - patients / controls or disease stage) is modeled as a linear combination of the MPIs (model parameters). The model

Table 5.4: The most relevant MPIs obtained by LDA approach and LASSO regression* (bolded MPIs are the ones selected by both approaches)

	Patients/Controls		Disease stage (HY)	
#	LDA	LASSO	LDA	LASSO
1.	GYRO-SSI TT-D-r	**GYRO-SSI TT-D-l**	**EMG-MAV GPP-HL-r**	**GYRO-SSI TT-D-l**
2.	**GYRO-SSI TT-D-l**	**EMG-MAV GPP-EL-l**	EMG-MAV TT-P-r	**EMG-MAV RH-EF-r**
3.	**EMG-MAV GPP-EL-l**	**EMG-MAV TT-D-r**	**GYRO-SSI TT-D-l**	**GYRO-RAN TT-D-l**
4.	**EMG-MAV GPP-HL-r**	**EMG-MAV GPP-HL-r**	**EMG-MAV RH-EF-r**	**EMG-MAV GPP-HL-r**
5.	**EMG-MAV TT-P-r**	**GYRO-SSI GPP-EL-l**	**GYRO-RAN TT-D-l**	**EMG-MAV GPP-EL-r**
6.	**GYRO-SSI GPP-EL-l**	GYRO-RAN GPP-HL-l	**EMG-MAV GPP-EL-r**	**EMG-MAV TT-D-r**
7.	**GYRO-RAN TT-D-l**	**GYRO-SSI GPP-HL-r**	**EMG-MAV TT-D-r**	EMG-MAV RH-EE-r
8.	GYRO-SSI GPP-HL-l	**GYRO-RAN GPP-EL-l**	**EMG-MAV RH-EE-l**	GYRO-RAN GPP-HL-r
9.	**GYRO-RAN GPP-EL-l**	**GYRO-RAN TT-D-l**	EMG-MAV GPP-HL-l	GYRO-RAN TT-D-r
10.	GYRO-RAN TT-D-r	**EMG-MAV TT-P-r**	GYRO-SSI GPP-HL-l	EMG-MAV TT-P-l
11.	EMG-MAV GPP-HL-l	EMG-MAV RH-EF-l	EMG-MAV RH-EF-l	**EMG-MAV RH-EE-l**
12.	**EMG-MAV TT-D-r**	GYRO-SSI RH-EF-r	GYRO-RAN GPP-HL-l	GYRO-RAN TT-P-l
13.	**GYRO-SSI GPP-HL-r**	GYRO-SSI TT-P-r	GYRO-SSI TT-D-r	EMG-MAV TT-D-l

*MPIs are listed in the format MPI movement-hand (r-right or l-left)

parameters with strongest dependence of the response variable will have higher coefficients, while the coefficients corresponding to the less important parameters will weight towards zero. In such way, we select the most important model parameters (corresponding MPIs) according to the classification task of interest. Results of both techniques, LDA and LASSO, giving the 13 most relevant MPIs (out of 84 MPIs in total), and for the classification criterion between groups of interest, are listed in the Table 5.4.

Table 5.4 shows that the 13 most relevant MPIs (out of 84 MPIs) are: GYRO-SSI, GYRO-RAN and EMG-MAV extracted mostly from the movements of object grasping, pick and place (GPP-EL and GPP-HL) and tapping test movements (TT-P and TT-D). The list of the most relevant MPIs is not the same in case of LDA and LASSO regression, but the majority of representative MPIs are selected by both methods (marked as bold text in the Table 5.4). Such result can be a consequence of the adjustment of regularization parameter $\lambda \in [0.01 - 0.5]$ during LASSOs regression. This parameter determines the strength of the penalty. As λ increases, more coefficients of the model are reduced to zero, hence more parameters (MPIs) are excluded from the model.

According to our tests of a new feature space (another outcome of the LDAs approach), the minimum number of synthetic features for successful classification is two. This is determined based on the eigenvalues obtained from the LDAs method. Synthetic features are obtained as a linear combination of all original MPIs in the way to emphasize the separation between classes. While these new synthetic features (f1 and f2) have the power to differentiate the different conditions in the data (Fig. 5.7(c) and 5.7(d)), they are more opaque in terms of communication and understanding for the medical doctors and therapists, as they do not correspond to a specific, physically-interpretable MPI.

5.4.2 Classification: diagnosis and monitoring evaluations

In this section, we present how designed MPIs can be used to differentiate between the groups of interest. We investigated two distinct classification problems in order to sup-

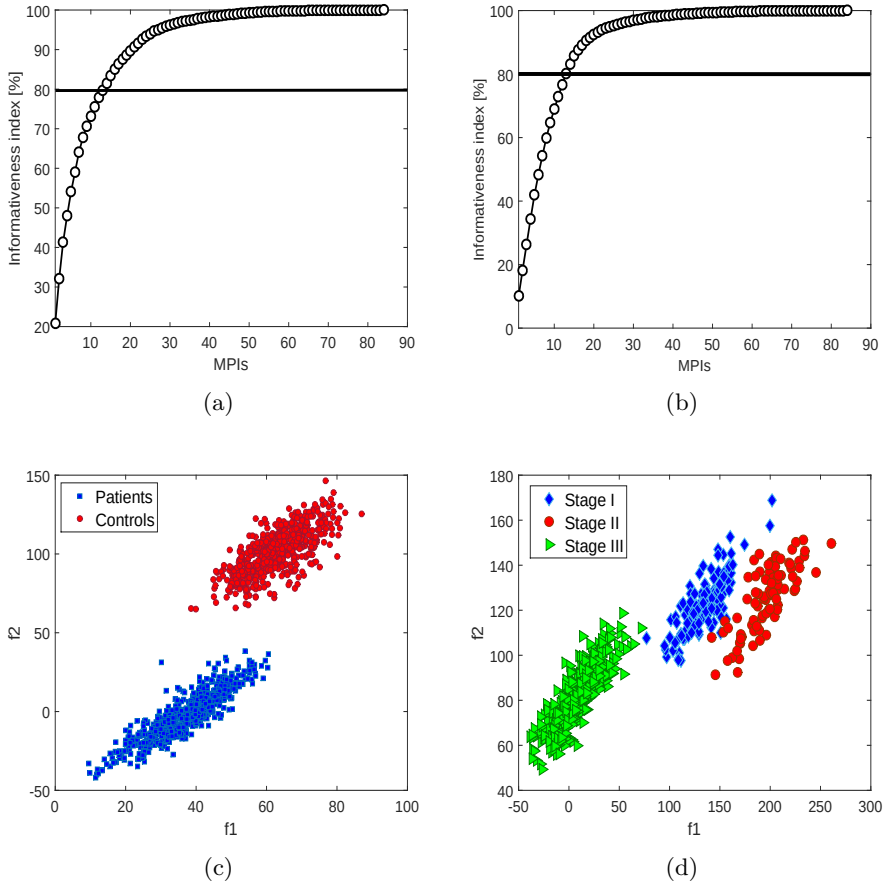


Figure 5.7: LDAs Informativeness index: (a) patients-controls and (b) disease stages. Data samples across groups of interest in the new reduced 2-dimensional space: (c) patients-controls and (d) disease stages. The synthesized MPIs can successfully differentiate the different groups of subjects and conditions.

port the diagnosis (patients against controls) and progress monitoring (disease stages). The diagnosis task is posed as discriminating the PD patients from the healthy controls, based on the measured values of MPIs, which is a well known binary classification problem. We define the monitoring task as discerning among the three severity stages in PD patients, which is the multi-class classification problem. Multi-class disease stage classification problem we reduced to three simple binary classification problems, one for each stage, in a common "one vs all" manner (Rifkin and Klautau [2004]).

To obtain the desired classifiers for diagnostic and monitoring purposes, we employed six common classification approaches: Logistic Regression, Decision Trees, Support Vector Machines (with RBF kernel), K-nearest neighbours (with number of nearest neighbours k=10), Naive Bayes and Neural Networks (multilayer perceptron with two hidden layers containing four nodes each).

Classifiers were built for four tasks: (i) PD patients vs controls (PD vs C.); (ii)

Table 5.5: Performance of six classification approaches in diagnostic and monitoring tasks for two sets of MPIs. All approaches are very successful on the given tasks, although K-Nearest Neighbor and Neural Networks appear to be the best performers.

	ORIGINAL (FULL) SET (84 MPIs)				SELECTED SUBSET (13 MPIs - LDA)			
Classifier	PD vs C.	Disease Stages			PD vs C.	Disease Stages		
		I vs II&III	II vs I&III	III vs I&II		I vs II&III	II vs I&III	III vs I&II
Logistic Regression	1 (0)	1 (0)	1 (0)	1 (0)	0.9967 (0.0034)	0.9942 (0.0088)	0.8969 (0.0569)	0.9961 (0.0074)
Decision Trees	0.9905 (0.0114)	0.9670 (0.0286)	0.9499 (0.0582)	0.9649 (0.0441)	0.9823 (0.0091)	0.9542 (0.0504)	0.8840 (0.1074)	0.9308 (0.0344)
Support Vector Machines	1 (0)	1 (0)	1 (0)	0.9993 (0.0022)	0.9967 (0.0039)	0.9927 (0.0072)	0.8759 (0.0835)	0.9972 (0.0028)
K-Nearest Neighbors	1 (0)	0.9999 (0.0002)	1 (0)	1 (0)	0.9981 (0.0039)	0.9983 (0.0031)	0.9899 (0.0140)	0.9956 (0.0077)
Naive Bayes	0.9948 (0.0037)	0.9908 (0.0078)	0.9757 (0.0269)	0.9743 (0.0202)	0.9878 (0.0056)	0.9903 (0.0060)	0.9158 (0.0371)	0.9798 (0.0170)
Neural Networks	1 (0)	1 (0)	0.9997 (0.0009)	0.9978 (0.0070)	0.9923 (0.0141)	0.9910 (0.0162)	0.9769 (0.0336)	0.9971 (0.0034)

stage I vs stages II and III PD; (iii) stage II vs stages I and III PD and (iv) stage III vs stages I and II PD, and by using two sets of MPIs: (a) original (full) set of 84 MPIs; and (b) set of 13 MPIs selected by LDA in Table 5.4. As a criterion of the classification success, the Area under the curve (AUC) in the case of Receiver operating characteristic curve (ROC) is calculated (Fawcett [2006]). ROC curve represents the graph of the true positive rate (TPR) against the false positive rate (FPR). AUC is the calculated surface area under the ROC curve. AUC values that indicate high-performance classifiers are in the range [0.80 - 1]. The performance of each classifier is assessed in a (10-fold) cross-validation procedure, and the results are provided in the Table 5.5 in form of a *mean (standard deviation)* calculated from 10 folds.

Table 5.5 shows that, the AUC values for all employed classification approaches are very high (near or equal to the perfect score of 1), suggesting that reliable decisions can be made by using the proposed MPIs. The most difficult task appears to be discerning the stage II patients from stages I and III PD, based on the selected subset of 13 MPIs. However, K-Nearest Neighbor and Neural Network classifiers seem to achieve quite consistent high performance under all tested conditions. Also, using only the 13 MPIs instead of all 84 results in just a slight reduction in performance, providing another evidence in favor of informativeness of the selected MPIs.

5.4.3 Left-right side analysis

In the PD, one side of the body is more affected than the other. Furthermore, the first symptoms of the disease are observed on a particular body side. Along with the disease progress, both sides become affected, but the side on which PD symptoms were first de-

tected, is always affected more. The quantitative assessment of the difference between left and right side of the body would be significant information for the neurologists, since they cannot evaluate it directly or using subjective clinical scales. Consequently, we want to investigate the differences in the movement performance with left and right hand, relying on the proposed MPIs. Our assumption is that those differences are negligible in control subjects, while they can become quite large for Parkinson's patients, depending on the disease stage.

To investigate which MPIs illustrate the differences in the performance of the left and right hand at patients and similar performance of the both hands in controls, statistical comparison has been performed. The choice of statistical tests depends on the data distribution. For data with a normal distribution, the ANOVA test is the appropriate choice. Otherwise, its nonparametric equivalent, Kruskal-Wallis test (Field [2009]) has to be applied. We performed the Kolmogorov-Smirnov test to assess the normal distribution hypothesis. The test rejected the normal distribution hypothesis with a 0.05 significance level. Consequently, two-sided Wilcoxon rank sum test is applied between the MPI values obtained with the left and right hand. There are forty-two MPIs in total for each hand - seven different MPIs for six movements. Three groups of interest have been considered (patients with the right side affected, patients with the left side affected and controls). For the disease stage analysis, both groups of the left and right side affected patients are additionally divided into the first three stage groups according to the Hoehn and Yahr (HY) (Goetz et al. [2004]).

The corresponding MPI is considered as relevant for the left-right side analysis between patients and controls if it satisfies the following conditions: (i) Patients group: (a) if the difference between the MPI values for the left and right hand is statistically significant ($p<0.05$) and (b) the left hand MPI values are larger than the right hand MPI values (for the right side affected patients) and the opposite for left-side affected patients; (ii) Controls: if the difference between the MPI values for the left and right hand is not statistically significant ($p>0.05$).

Results of the statistical analysis suggest that 14 MPIs out of 84 MPIs in total are relevant for the left-right side analysis between patients and controls: all EMG MPIs for GPP-EL and GPP-HL, two EMG MPIs for RH-EE and RH-EF movements and all ACC and GYRO MPIs for RH-EF movement. Such result indicates that EMG MPIs for grasping, pick and place movements are the most relevant for the left-right side analysis, as well as MPIs extracted from the rotation of the hand movement while the elbow is flexed.

Figure 5.8(a) illustrates the mean and standard deviation graph for controls and right side affected patients for ACC-SSI MPI (RH-EF movement). It can be seen the mean MPI values are almost the same in the case of controls, while in patients, the mean MPI value for the left hand movement is larger than for the right hand movement. Such outcome is expected, since the right side is affected by PD and consequently, has lower performance.

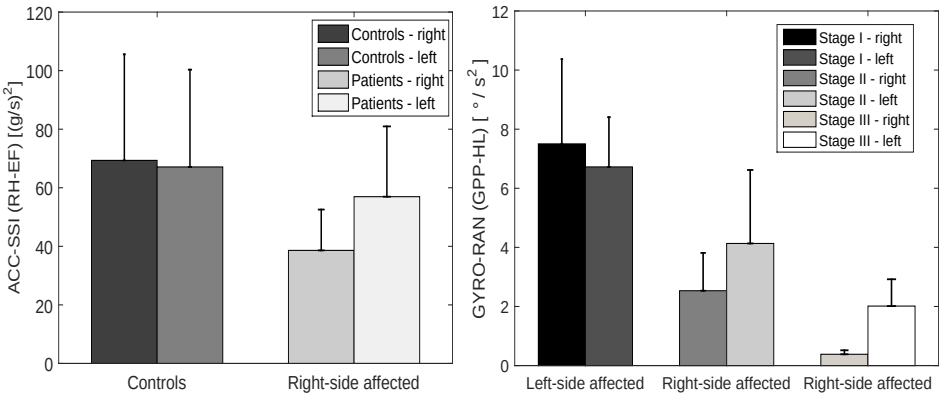


Figure 5.8: ACC-SSI MPI (RH-EF movement) for controls and right side affected patients (a) and GYRO-RAN (GPP-HL movement) for different disease stages (b). The mean MPI values for the left and right hand are similar in controls opposite to the patients (a). The mean MPI values decrease from the first to the third stage and their difference between the left and the right hand increases (b).

The same statistical tests were conducted for the left-right side analysis between disease stages. Statistical investigation is based on the following conditions: (i) the difference between the MPI values of the left and right hand is statistically significant ($p<0.05$); (ii) the left-hand MPI values are larger than the right-hand MPI values (for the right side affected patients) and the opposite for left-side affected patients and (iii) MPI values decrease with more severe disease stage, while their differences between the left and the right hand increase.

The results of the statistical analysis suggest that 11 MPIs out of 84 MPIs in total are relevant for the left-right side analysis between disease stages: EMG-VAR and all ACC MPIs for RH-EF movement, ACC-SSI, ACC-RAN, GYRO-SSI and GYRO-RAN for GPP-EL movement, ACC-RAN, GYRO-SSI and GYRO-RAN for GPP-HL movement and ACC-SSI for TT-P movement. It turns out that the ACC and GYRO MPIs for RH-EF, GPP-EL and GPP-HL are the most common MPIs to evaluate the difference in performance between left and right hand across the disease stages.

Figure 5.8(b) illustrates the mean and standard deviation graph across disease stages for GYRO-RAN MPI (GPP-HL movement). It can be seen that the mean MPI values decrease from the first to the third stage and their difference between the left and the right hand increases. Such result suggests that differences in the performance of the left and right hand become larger with the disease progression. It can be seen that in the case of the left-side affected group (first stage) the MPI values are greater for the right hand. The situation is opposite for the right-side affected group of the second and third disease stage. In both cases, MPI values are greater for the hand less affected by the disease, which is an expected outcome.

5.4.4 Correlations with clinical scales

Our MPIs have shown the potential to classify different groups of subjects and conditions. Classification procedure represents the basis for the further development of the decision-making systems to support diagnosis (classification between patients and controls) and disease progress evaluations (disease stage classification). Particular MPIs have demonstrated the relevance for the left-right side analysis. In this section, we want to investigate whether the proposed MPIs are correlated with clinical test and scales. This is particularly important for the possible inclusion of the proposed MPIs into medical protocols.

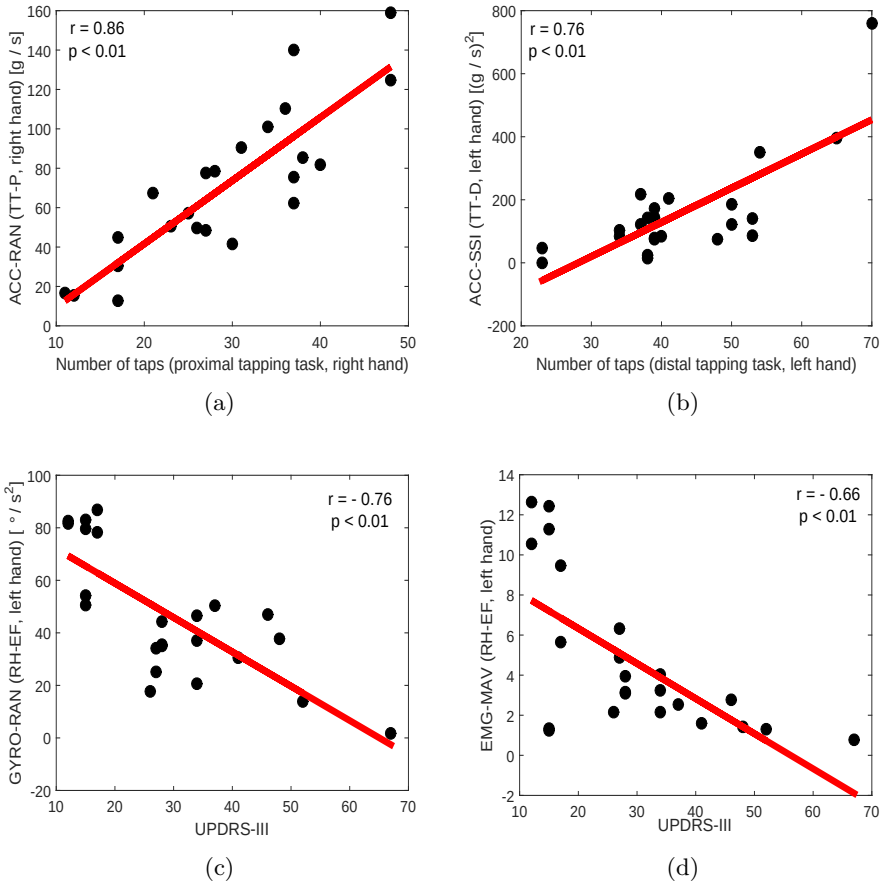


Figure 5.9: Scatter plots of the correlation between particular MPI and tapping test (a-d)

The correlation analysis is carried out between the proposed MPIs and tapping test (Potter-Nerger et al. [2009]) and UPDRS-III clinical scale (Goetz et al. [2008]). The tapping-test outcomes and UPDRS-III values are obtained as a result of a neurologist's evaluation. Correlations were calculated using Pearson's correlation coefficient r (higher values of r indicate better correlation), along with the p-value. Scatter plots in Figure 5.9 illustrate the correlation between selected MPIs and clinical parameters,

where the line represents the regression curve. It can be seen that the selected MPIs have a positive correlation with the tapping test (Figure 5.9(a), 5.9(b)), more concretely with the number of taps in two cases of the tapping task (procedure of the tapping task is previously explained in the Section 5.2.2). This is expected since the patients who have higher values of MPIs potentially can achieve a larger number of taps within defined time interval (30 seconds). On the other side, our MPIs have a negative correlation with the UPDRS-III scale (Figure 5.9(c), 5.9(d)), since the lower values of our MPIs and higher values on this scale indicate a more severe state of the patient i.e. more advanced disease stage.

Results of the correlation analysis regarding the tapping test have shown that the most correlated MPIs are the ones extracted from the tapping test movements (TT-P and TT-D). Such result is expected, since the same movements are tested during clinical protocol and our sensor measurements. Those MPIs refer to all ACC and GYRO MPIs of both, left and right hand movements. In addition to the tapping test movements, ACC and GYRO MPIs from the right-hand RH-EE and GPP-EL movements, as well as from the left hand RH-EF movement have high values of Pearson's correlation coefficient r. MPIs extracted from EMG signals are mostly poorly correlated with tapping test ($r < 0.5$), except EMG-MAV and EMG-WC MPIs in the case of the left-hand TT-P movement.

Results of the correlation analysis regarding the UPDRS-III scale show that the most correlated MPIs are the ones extracted from the rotation of the hand movements (RH-EE and RH-EF). Those MPIs refer to all EMG, ACC and GYRO MPIs of both, left and right hand movements. In addition to the rotation of the hand movements, ACC MPIs from the right hand TT-P movement, as well as GYRO-RAN MPI from the right hand GPP-HL movement have high values of Pearson's correlation coefficient r. Since higher values of r indicate better correlation, those MPIs are very good in terms of correlation with clinical scales.

Table 5.6. summarizes the importance of the MPIs and tested movements across nine criterions of clinical interest. GYRO-SSI and GYRO-RAN MPIs are relevant according to all criterions. Particular EMG MPIs are important for the classification aspect and left-right side analysis (both conditions - patients vs. controls and disease stages), while the ACC MPIs are of interest for the left-right side analysis and correlation with clinical scales. Among tested movements, object grasping, pick and place (both variations - easy and heavy load) turn out to be the most relevant for listed clinical aspects. Reliability analysis has demonstrated the high reliability for all proposed MPIs across all movements (Table 5.6).

5.5 Summary and discussion

In this chapter, we have presented an approach for quantitative movement analysis, based on the arm/hand movement data acquired with an EMG sensor. Our results

Table 5.6: Importance of the MPIs and tested movements across criterions of clinical interest

		MPIs							Movement (left and right hand)					
Criterion		EMG			ACC		GYRO		RH		GPP		TT	
		mav	var	wc	ssi	ran	ssi	ran	EE	EF	EL	HL	P	D
1.	Reliability	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2.	Classification patients-controls LDA	✓					✓	✓			✓	✓	✓	✓
3.	Classification patients-controls LASSO	✓					✓	✓		✓	✓	✓	✓	✓
4.	Classification disease stages LDA	✓					✓	✓	✓	✓	✓	✓	✓	✓
5.	Classification disease stages LASSO	✓					✓	✓	✓	✓	✓	✓	✓	✓
6.	Left-right side analysis patients-controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
7.	Left-right side analysis disease stages		✓		✓	✓	✓	✓		✓	✓	✓	✓	
8.	Correlation - tapping test				✓	✓	✓	✓	✓	✓	✓		✓	✓
9.	Correlation - UPDRS-III	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	

show that the proposed approach has the potential to be adopted by therapists, to enhance objectivity and precision, during the diagnosis / monitoring evaluations and bradykinesia assessment. At the same time, it opens the possibility of low-cost home rehabilitation for patients with the mild to moderate PD stages (I-III according to the modified HY clinical scale).

We have used a wireless armband sensor to acquire arm/hand movements defined by the PD protocol. We propose a set of 84 Movement Performance Indicator (MPI) to characterize acquired movements. We conducted a thorough analysis of the properties of these MPIs, to identify their importance in terms of relevant clinical aspects (Table 5.6): (i) reliability; (ii) classification between patients and controls and between disease stages (support to diagnosis and monitoring, respectively); (iii) left-right side analysis between controls and patients, as well as between disease stage groups and (iv) correlation with clinical scales (tapping test and UPDRS-III). The overall conclusion is that GYRO-SSI and GYRO-RAN MPIs are relevant according to all clinically-relevant criterions. Particular EMG MPIs are important for the classification aspect and left-right side analysis, while the ACC MPIs are of interest for the left-right side analysis and correlation with clinical scales.

The armband electromyographic sensor is worn on the forearm and collects the data from the four groups of muscles - flexors, extensors, internal and external forearm muscles (Section 5.3.1, Fig. 5.5). One very important conclusion is that external forearm muscles of both hands in PD patients have demonstrated the lowest performance of all forearm muscles in the sense of the muscle activity compared with a control group. This result suggests that external forearm muscles are the most affected by the Parkinson's disease. Such result is derived from our sensor data, but requires additional clinical testing and confirmation.

Finally, we conclude that sensor data collected from the wireless armband device successfully addressed the same set of relevant aspects in PD like the sensor glove data analised in Chapter 4. Even more, in this study, we have performed the left-right side analysis, which is not feasible with the sensor glove data, due to its right-hand design. Consequently, our results suggest that the wireless armband sensor can be a possible alternative for high-cost data glove. However, the experimental setup, tested movements and extracted MPIs are different in accordance with sensor choice. The advantage of the sensor glove data over the armband device is the quantification of the fine finger movements.

Chapter 6

Kinect and EMG-based quantitative approach for progress monitoring of the stroke patients

In the previous three chapters, the focus was on the Parkinson's disease patients (Chapters 3, 4, 5). We have conducted the quantitative movement analysis of Parkinson's patients based on the sensor data. We have addressed three main groups of the rehabilitation movements: (i) full body movements (gait and large range upper body movements) acquired with Kinect device; (ii) fine hand movements acquired with data glove and (iii) arm/hand movements collected using the armband device. For each movement group, the corresponding set of quantitative movement measurements (MPIs) is defined, resulting in total with 10 MPIs for full body movements, 15 MPIs for fine hand movements and 84 MPIs for arm/hand movements. The thorough analysis of the properties of these MPIs is conducted, to identify their importance in terms of relevant clinical aspects: (i) reliability; (ii) classification between patients and controls and between disease stages (support to diagnosis and monitoring, respectively); (iii) left-right side analysis between controls and patients, as well as between disease stage groups and (iv) correlation with clinical scales (tapping test and UPDRS-III). The main purpose of the designed MPIs is to support the clinical evaluations related to the disease diagnosis and progress monitoring. This goal is achived by indentification of the different clinical groups of interest based on the extracted MPIs (patients vs. controls (support to diagnosis) and disease stage groups (monitoring support)). Hence, the data analysis is the group-oriented and not individually-based. Another reason for this approach arises from the fact that the patients' condition in the sense of movement performance changes very slow in PD, since the period between significant changes in

the movement performance is usually one to two years.
On the other side, in a post-stroke period, the patients' experience significant recovery in the case of the appropriate rehabilitation therapy. The period between the significant changes in the movement performance is approximately one to two weeks, if the patients attend rehabilitation practice every day. The well-known and mostly used clinical scale for evaluations of the movement performance in the post-stroke patients is Fugl-Meyer scale [Fugl-Meyer et al., 1974]. The outcome of this scale is only one number for all conducted clinical tests. Consequently, the scale is not informative enough and can be prone to the imprecise rating. The objective evaluation of the movement performance, based on the sensor data, can significantly improve the clinical monitoring assessments. Hence, the approach to the quantification of the movement performance after the stroke is patient-oriented and focused only on the progress monitoring. This means that the patients are monitored and analyzed individually based on the clinical and sensor measurements. The reports about their performance over time relying on the sensor data are provided to medical domain experts to support their clinical evaluations.
The experimental protocol for the movement examination in patients recovering from stroke consists of the upper body movements acquired with the Kinect device and arm/hand movements collected using the armband device. Both protocols are defined by an experienced physiatrist. The sensor recordings, along with the clinical scores are collected five times during the post-stroke rehabilitation period in order to keep track of the movement performance progress. Based on the collected sensor data, the following aspects are addressed later in the chapter: (i) the design of the MPIs for both groups of the examined movements, (ii) statistical analysis of the repeated sensor measurements, (iii) healthy-affected side analysis, (iv) correlation with clinical (Fugl-Meyer) scale and (v) design of an application for storing, visualization and interpretation of the sensor data and MPIs including the personal patients' profiles.

6.1 Proposed system structure

The proposed system structure for quantitative assessment of the large range upper body movements using the Kinect device and arm/hand movements collected with EMG armband device is illustrated in Figure 6.1. The properties of the Kinect and EMG armband device have been presented in the previous chapters (Chapter 3 and Chapter 5, respectively).

The first steps are the sensor calibration and the movement data collection. As a second stage, the sensor signals are pre-processed with low-pass filters to reduce the measurement noise. The MPIs from Kinect device are calculated from each separate movement, whereby the same segmentation procedure as the one presented in Section 3.3.1 is performed. The MPIs from EMG armband are extracted from all consecutive

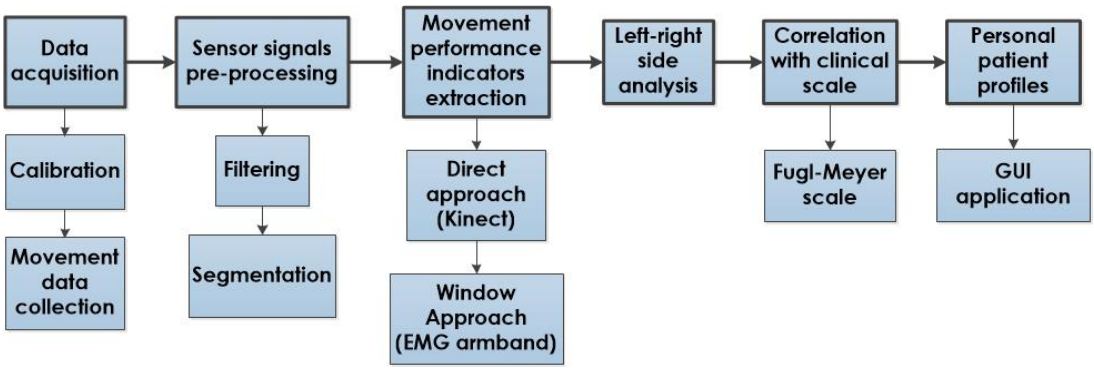


Figure 6.1: Proposed system structure

movements in one sequence at the same time. Hence, only the general segmentation procedure is performed to remove the non-informative signal parts at the beginning and at the end of the sensor signals. The MPIs for the quantification of the large range upper body movements are extracted based on the approach explained in Section 3.4. Particular MPIs are the same as in the case of Parkinson's patients and some MPIs are stroke-specific (Section 6.3). For characterizing the arm/hand movements, the window-based approach and the same MPIs as in the case of PD patients have been adopted (Sections 5.3 and 6.3).

Taken into account that the sensor recordings are repeated in the defined time periods, we conduct a statistical analysis of the repeated measurements to determine the internal cosistency of the sensor measurements and the reliability of the proposed MPIs (Section 6.4.1). In the case of stroke patients, the main focus is on the progress monitoring of the affected hand. The movement performance of the healthy hand is used as a referent measure. Consequently, here we do not examine the control group and we do not deal with the comparisons between the healthy subjects and patients, as it was the case in the previous chapters with focus on PD. The comparison is made only between the healthy and affected hand (Section 5.4.3). Correlation of the proposed MPIs with Fugl-Meyer scale ([Fugl-Meyer et al., 1974]) is presented in Section 6.4.3. Finally, we build an application for storing, visualization and interpretation of the collected sensor data and MPIs (Section 6.4.4). The application contains personal patients' profiles, along with their relevant clinical and sensor measurements over time. Thus, physiatrists can have the unified evidence about patients' progress.

6.2 Experimental procedure

6.2.1 Participants

The experimental group consists of three stroke patients with personal and disease characteristics listed in Table 6.1. The National Institutes of Health Stroke Scale

(NIHSS) and Barthel index (BI) represent clinical evaluation scores established at the time of the stroke occurrence. NIHSS gives the information about the stroke severity after the clinical neurological examination. The range of this score is $[0-42]$, whereby the larger number indicates more severe state. BI gives the information about the possibility of performing the everyday activities. The range of this index is $[0-100]$, whereby the zero value indicates the complete dependence on the other person during everyday tasks. Larger numbers suggest higher patients' independence.
All patients have been examined under the same conditions and they have performed five upper body movements and six arm/hand movements, instructed by an experienced physiatrist. The experimental protocol is presented in the Tables 6.2 and 6.3. The tested movements are chosen to closely reflect the patient's state in terms of motor performance aspect. The movements have been performed with both, the healthy and affected hand, respectively, and acquired using the Kinect and EMG armband sensor. Illustration of the experimental movements is given in Figures 6.2 and 6.3. Clinical measurements (Fugl-Meyer scale ([Fugl-Meyer et al., 1974]) are collected by an experienced physiatrist right after the sensor measurements. All patients were tested five times - the first four times, the period between the recordings was one week, while the last recording is made after one month from the fourth recording. During the first month, the patients attended the rehabilitation sessions every day. The rehabilitation session consists of the set of exercises, defined by the physiatrist. Hence, the first four recordings are made while the patients were performing the rehabilitation exercises and the last recording is conducted one month after the last rehabilitation session. During that month, the patients did not perform any exercises.

Table 6.1: Patient characteristics

Age (years), mean (SD)	58.33 (9.45)
Range	51-69
Gender (number of patients)	Males (3)
	Females (0)
The National Institutes of Health Stroke Scale (NIHSS), mean (SD)	7.33 (2.52)
Range, 0-42	5-10
Barthel index (BI), mean (SD)	66.67 (14.43)
Range, 0-100	50-75
Time after stroke (years), mean (SD)	2.33 (2.31)

6.2.2 Experimental protocol

The medical procedure adopted for evaluations in stroke includes a set of movements/exercises, in order to allow doctors to make a qualitative assessment of the patients' state and their recovery progress. The experimental protocol consist of the five upper body movements collected with Kinect device and six arm/hand movements,

Table 6.2: Acquired large range movements according to the experimental protocol

	Acquired large range movements according to the experimental protocol
1.	Hand goes from the ear to the hip (same body side) (upperbody1)
2.	Hand goes from the ear to the hip (different body side - diagonal) (upperbody2)
3.	Shoulder flexion-extension (upperbody3)
4.	Shoulder abduction-adduction (upperbody4)
5.	Elbow flexed at 90°: hands go up and down in the shoulder joint (upperbody5)

Table 6.3: Acquired arm/hand movements according to the experimental protocol

	Acquired arm/hand movements according to the experimental protocol
1.	Elbow flexed at 90°: Palm goes up and down (arm/hand1)
2.	Arm stretched: Palm goes up and down (arm/hand2)
3.	Elbow flexed at 90°: pronation and supination (arm/hand3)
4.	Arm stretched: pronation and supination (arm/hand4)
5.	Movement of object grasping, pick and place: easy load (arm/hand5)
6.	Movement of object grasping, pick and place: heavy load (arm/hand6)

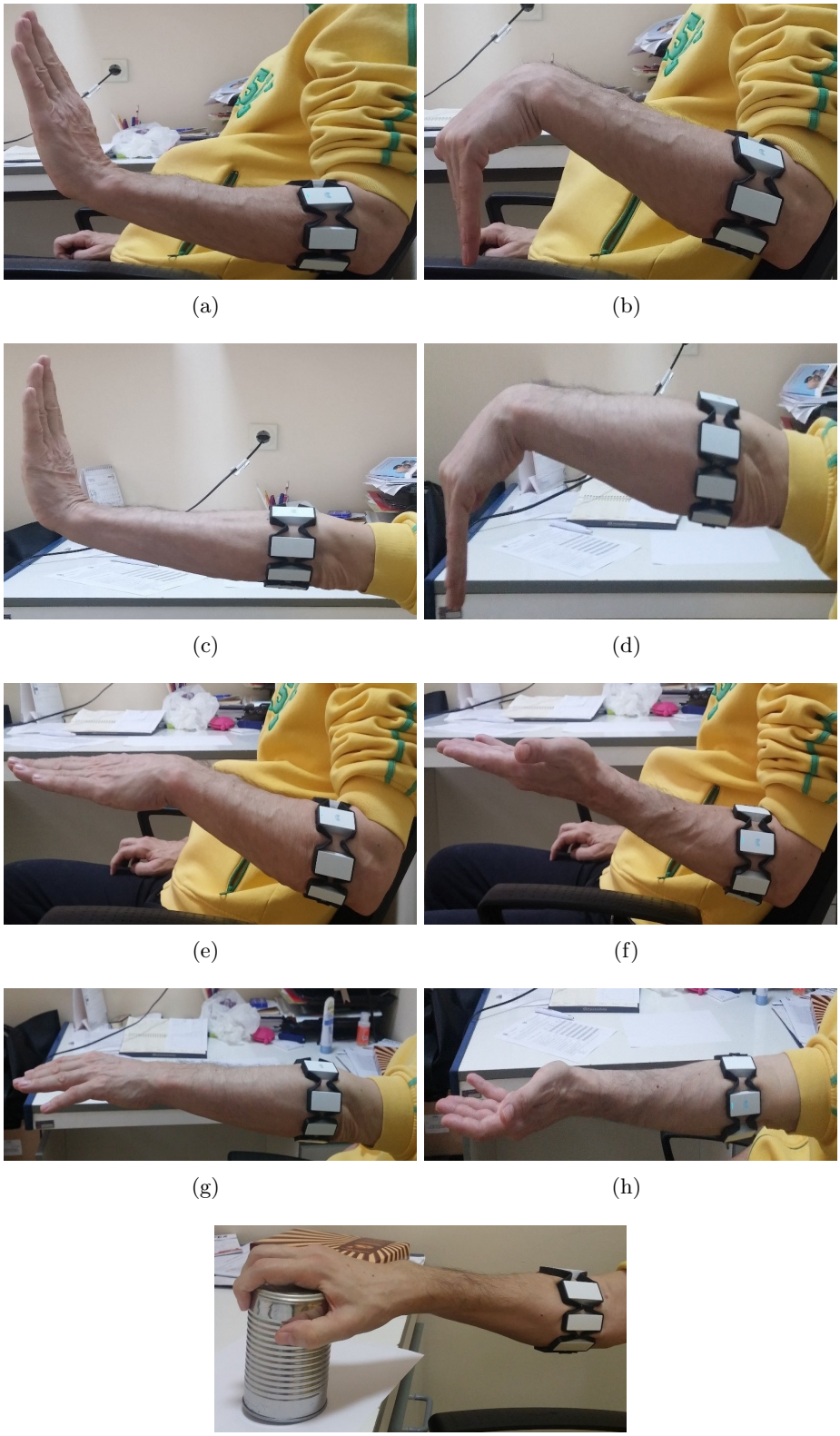
acquired with EMG armband device.

The upper body movements are listed in the Table 6.2 and illustrated in the Figure 6.2. All movements were repeated three times consecutively during the experiments. The first two exercises refer to the hand movement starting from the ear position and ending on the hip of the same (Figures 6.2(a) and 6.2(b)) or different body side (Figures 6.2(c) and 6.2(d)). The following two exercises are shoulder abduction-adduction (Figures 6.2(e) and 6.2(f)) and shoulder flexion-extension (Figures 6.2(g) and 6.2(h)). Those exercises are well-known in rehabilitation practice in general and represent the part of the PD protocol (Section 3.2.2), as well. The last movement is performed with the elbow flexed at 90° while hands go up and down in the shoulder joint (Figures 6.2(i) and 6.2(j)).

The first two arm/hand exercises illustrate the same task - palm goes up and down in two variations: elbow flexed at 90° - Figures 6.3(a) and 6.3(b)) and arm stretched - Figures 6.3(c) and 6.3(d)). The following two exercises represent the pronation-supination movement in the same two variations: elbow flexed at 90° - Figures 6.3(e) and 6.3(f)) and arm stretched - Figures 6.3(g) and 6.3(h)). The last two exercises represent the movement of object grasping, pick and place for the case of easy and heavy load (Figure 6.3(i)).

The clinical measurements ([Fugl-Meyer et al., 1974]) are collected by one experienced rater immediately before the sensor measurements. All measurements have been performed in the hospital settings for outpatients. The clinician was present during the sensor measurements in order to monitor the patient state. The clinical values are collected in accordance with the Fugl-Meyer scale ([Fugl-Meyer et al., 1974]).

Figure 6.2: Hand goes from the ear to the hip (same body side): (a) and (b); Hand goes from the ear to the hip (different body side - diagonal): (c) and (d); Shoulder flexion-extension: (e) and (f); Shoulder abduction-adduction: (g) and (h) and Elbow flexed at 90°: hands go up and down in shoulder joint (i) and (j)



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Figure 6.3: Elbow flexed at 90°: Palm goes up (a) and down (b); Arm stretched: Palm goes up (c) and down (d); Elbow flexed at 90°: pronation (e) and supination (f); Arm stretched: pronation (g) and supination (h) and Movement of object grasping, pick and place easy/heavy load (i)

6.3 An approach to movement characterization

6.3.1 Upper body movements characterization

We have defined seven different quantitative measurements (MPIs) to characterize five upper body movements (Table 6.4). The extracted MPIs for each movement are listed in the Table 6.4. Three of them have been previously used for the quantification of the upper body movements in PD (Chapter 3). They refer to the shoulder angle Range of Motion (ROM), Movement speed (MS) and Symmetry Ratio (SR). Four additional MPIs are the following: Vertical distance between hands (VDBH), elbow angle ROM, Vertical shoulder-elbow distance (VSED) and Mean shoulder angle (MSA) (Table 6.4).

The Range of Motion (ROM) represents an angle of the movement relative to a specific body axis, which can be measured at various joints such as shoulder, elbow, knee, etc. We measure the evolution of the shoulder angle during the movement in relation to the longitudinal body axis. Elbow angle is measured in the elbow joint, between the upper arm and the forearm lines. In relation to the angle measurement, we define two possible MPI outcomes: (i) the ROM value, where we take the value of the angle in the final movement position and (ii) the mean value of the angle during the movement, as in the case of MSA MPI.
Figure 6.4 illustrates the evolution of the elbow angle profiles during shoulder abduction-adduction movements. According to the movement definition, arms are stretched in the elbow during the whole movement. This means that elbow angle should be close to the 180°. Fig. 6.4 shows that for the healthy arm, elbow angle takes values in the range $[160° - 175°]$, which is an expected result. On the other side, the affected arm has demonstrated significantly weaker performance. Elbow angle values for the affected arm are in the range $[110° - 160°]$. Such result suggests that the ROM of elbow angle is a good indicator of the movement performance and potential quantitative measurement of the difference between healthy and affected hand.

Table 6.4: Calculated MPIs from the upper body movements

	Movement	Calculated MPIs				
1.	upperbody1	ROM shoulder	MS	SR		
2.	upperbody2	ROM shoulder	MS	SR		
3.	upperbody3	ROM shoulder	MS	SR	VDBH	ROM elbow
4.	upperbody4	ROM shoulder	MS	SR	VDBH	ROM elbow
5.	upperbody5	VSED	MS	SR	VDBH	MSA

We calculate the mean speed V during the movement according to the Eq. 3.10. Angular velocity profiles can demonstrate the symmetry of the movements. In motor control, the Symmetry Ratio (SR) [Plamondon, 1995; Gribble and Ostry, 1996; Bullock and Grossberg, 1991; Mirkov et al., 2002] is defined as the ratio between acceleration (t_{ACC}) and deceleration (t_{DEC}) times (obtained from the angular velocity profile),

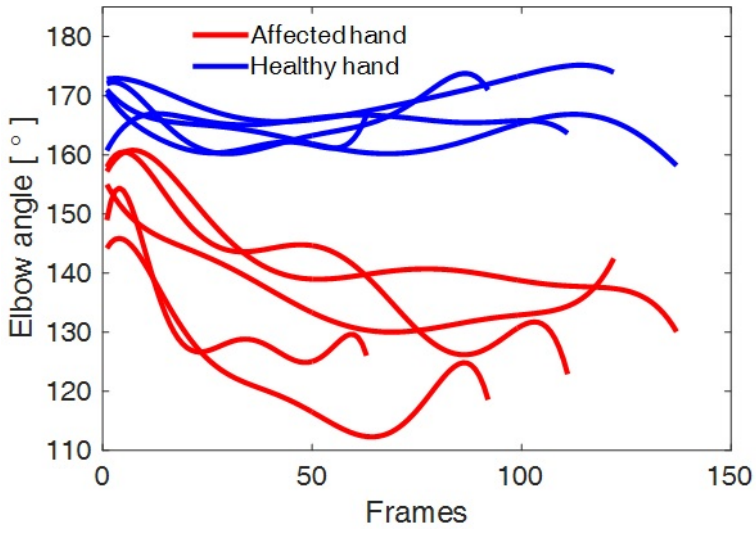


Figure 6.4: Evolution of the elbow angle profiles during shoulder abduction-adduction movements

during one movement. An example of the angular velocity profile for shoulder angle, along with the calculation of the ROM is presented in Figure 6.5. For normal movements, the SR has values around 1. In the case of the impaired movements, SR has values significantly larger or smaller than 1, like it is shown in the Figure 6.5.

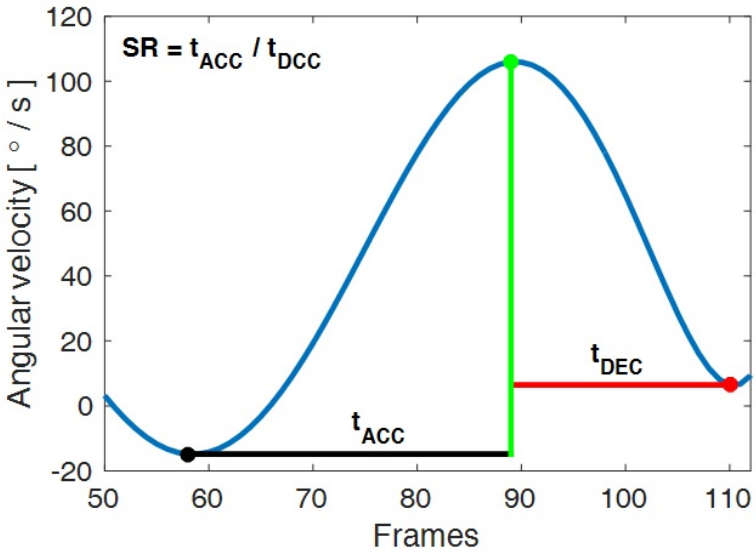
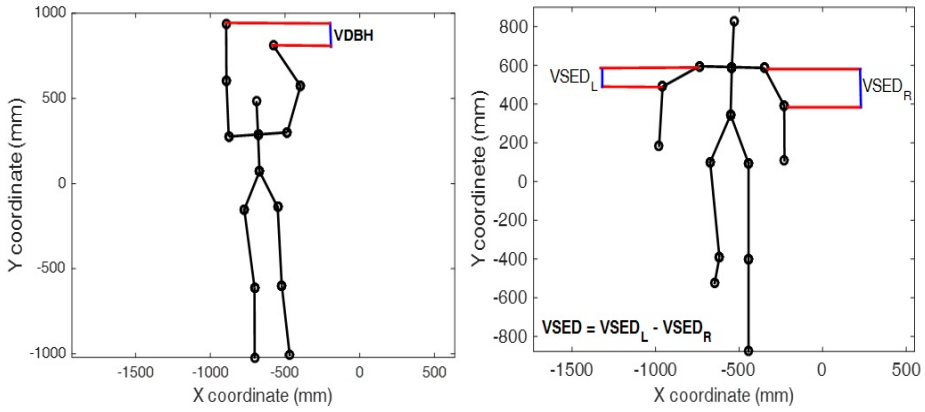


Figure 6.5: Evolution of the shoulder angular velocity profiles during the shoulder abduction movement and SR calculation

The Vertical distance between hands (VDBH) is calculated as a difference in y-coordinate of the left and right hand joint at the final movement position (Figure

6.6(a)). In normal movements, this difference should be close to zero, while in the case of the impared movements, it becomes significant (Figure 6.6(a)). In the same manner, the Vertical shoulder-elbow distance (VSED) is calculated as a difference of a y-coordinate shoulder-elbow differences of the left and right hand at the final movement position (Figure 6.6(b)). This MPI is calculated from the upperbody5 movement. According to the movement definition, the elbow should be flexed at 90°, which means that the vertical distance between shoulder and elbow of both hands should be zero. Figure 6.6(b) clearly illustrates that this is not the case for a stroke patient, whereby the difference is larger for the affected hand.



(a) (b)

Figure 6.6: Calculation of the VDBH MPI during the upperbody4 movement (a) and VSED MPI during the upperbody5 movement (b)

We have described seven different MPIs extracted from the Kinect data to quantify the upper body movements of the stroke patients. These MPIs will be used later on to support the clinical evaluations in stroke and for the design of the personal patients' profiles inside the GUI application intended for storing, visualization and interpretation of the sensor measurements.

6.3.2 Arm/hand movements characterization

Similarly to what we have done for the upper body movements, we define seven basic measurements to characterize the arm/hand movements. The same basic measurements as in the case of PD patients, explained in the section 5.3.1, have been extracted from the armband sensor signals using the window approach (5.3). They successfully address the differences in movements performed with healthy and affected hand. The MPIs for evaluation of the arm/hand movements in stroke patients are listed in Table 6.5.

The comparative analysis between the healthy and affected hand across six collected movements and eight EMG channels, as well as three axes of accelerometer

Table 6.5: Calculated basic measurements from the arm/hand movements

	Calculated basic measurements from the arm/hand movements
1.	Mean absolute value from EMG signal (EMG-MAV)
2.	Variance from EMG signal (EMG-VAR)
3.	Waveform change from EMG signal (EMG-WC)
4.	Simple square integral from accelerometer signal derivative (ACC-SSI)
5.	Range from accelerometer signal derivative (ACC-RAN)
6.	Simple square integral from gyroscope signal derivative (GYRO-SSI)
7.	Range from gyroscope signal derivative (GYRO-RAN)

and gyroscope, have been conducted in order to investigate whether the EMG data from particular channels and IMU data from particular axes are more discriminative than others. The amplitude of the sensor signals was used as the comparison criteria, whereby the signal amplitudes (after filtering) were significantly larger for the healthy hand than in the case of the affected hand. In patients with the right hand affected, the results are indicative of significant differences in the channels 5, 6 and 7, while for the left-hand affected patients the channels 1, 2 and 3 demonstrate the larger performance differences. It can be seen from the Figure 5.5, that those electrodes cover the same group of the forearm muscles in the case of both hands, as expected. The covered region includes internal forearm muscles and the part of the flexors and extensors. Regarding the axes of accelerometer and gyroscope, for the first four arm/hand movements (Table 6.3) the y-axis underlines the larger differences, while in the case of the arm/hand5 and arm/hand6 movements, it is the z-axis. Again, as it was the case in the Chapter 5, we extract the MPIs from derivatives of the accelerometer and gyroscope signals since they enlarge the differences.

Figure 6.7 illustrates different arm/hand MPIs across several consecutive recordings. Patients show different movement performance from one recording to another. Patient 3 (Figure 6.7(a)) has increasing performance during the first four recordings, while in the fifth recording, his performance drops. Similar pattern is present in the case of Patient 1 (Figure 6.7(c)). The reason can be the fact that the last recording is made after one month from the previous recording. During that period, the patients were inactive in the sense of rehabilitation therapy. On the other side, Patient 2 improves his performance during the first three recordings, but after, his performance remains almost the same in the following recordings. Such results for all three patients are in accordance with clinical (Fugl-Meyer) scale.

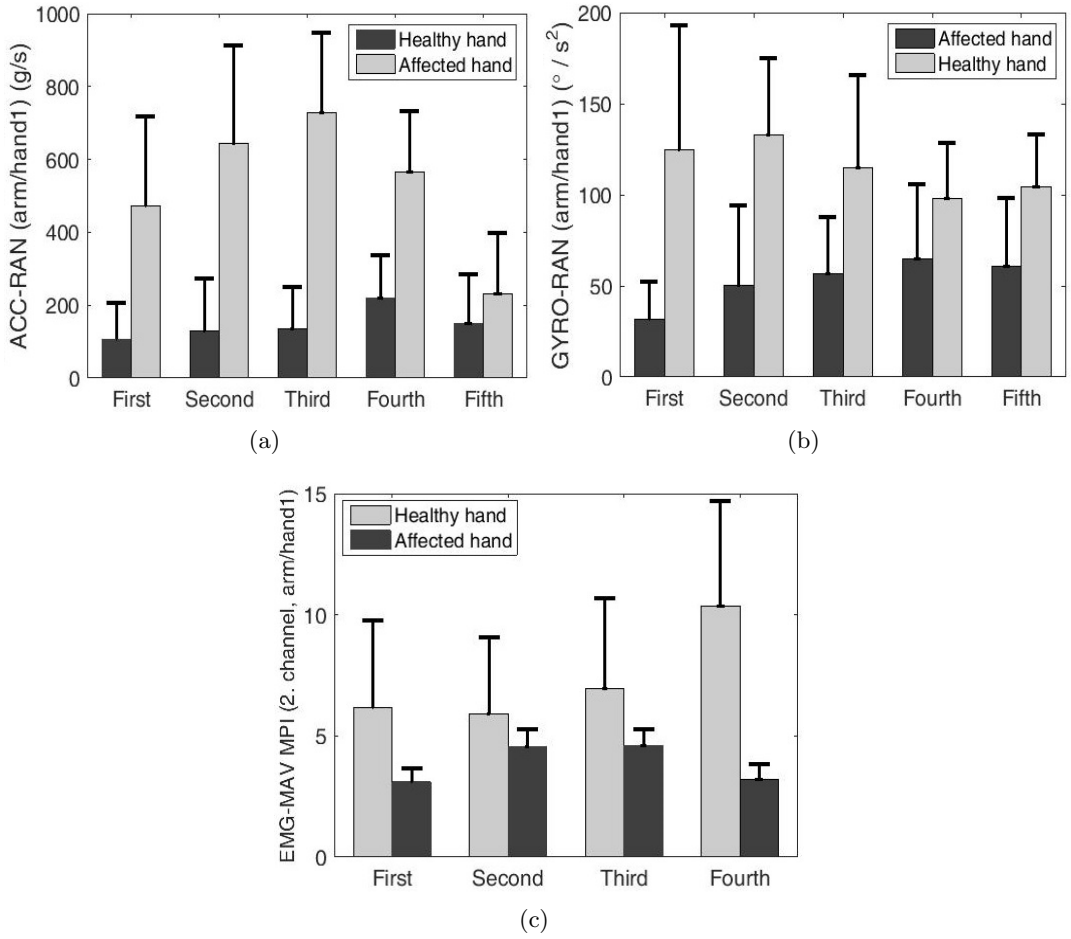


Figure 6.7: ACC-RAN - Patient 3 (a), GYRO-RAN - Patient 2 (b) and EMG-MAV - Patient 1 for the affected and healthy hand (arm/hand1 movement) across consequtive recordings

6.4 Results

6.4.1 Statistical analysis of the repeated measurements

As aforementioned in the section 6.2.1, the sensor measurements were collected five times in a row - the first four measurements are collected between one-week interval, while the last measurement is performed one month after the fourth measurement. Additionally, in the time of the first four recordings, the patients have attended the rehabilitation therapy every day. After the fourth recording, they stopped the therapy and their performance is measured again after one month. In this section, we will focus on the statistical analysis of the repeated measurements in the context of: (i) internal consistency of the sensor measurements and (ii) reliability of the extracted MPIs, both from Kinect and wireless armband sensor.

Internal consistency of the sensor measurements is assessed using Cronbach's alpha

parameter [Field, 2009]. In the case of the Kinect sensor measurements, Cronbach's alpha parameter was investigated for five recorded movements (Figure 6.2), fifteen collected joints (Figure 3.2) and three coordinates (X, Y and Z, Figure 3.3). The data set for internal consistency analysis consists of three patients. All obtained Cronbach's alpha parameters across different movements, joints and coordinates for the three patients data have values within the range $[0.95 - 0.99]$. Values of Cronbach's alpha parameter close to one indicate the high consistency of the Kinect sensor measurements.

In the same manner, the internal consistency is calculated for the armband sensor measurements across six movements (Figure 6.3) for EMG data (8 channels) and IMU data (3 axes) based on the three patients dataset. The obtained values of the Cronbach's alpha parameters within the range $[0.87 - 0.98]$ confirmed the high internal consistency of the armband sensor measurements, as well.

In order to investigate the reliability of the extracted MPIs, the test-retest method for the reliability analysis [Field, 2009] has been applied. The test-retest method correlates the scores across repeated tests and the reliability is assesed using Intraclass correlation coefficient (ICC) [Field, 2009]. ICC has a value inside range [0 - 1], whereby the values closer to 1 indicate higher reliability. Reliability results are shown in the Table 6.6 for the Kinect (upper body) MPIs and in the Table 6.7 for the armband sensor (arm/hand) MPIs.

Table 6.6: Test-retest reliability for the upper body MPIs

	ICC reliability parameter						
Movement	ROM shoulder	MS	SR	VDBH	VSED	ROM elbow	MSA
upperbody1 R	0.89	0.84	0.89	/	/	/	/
upperbody2 R	0.94	0.94	0.82	/	/	/	/
upperbody3 R	0.79	0.88	0.96	0.92	/	0.96	/
upperbody4 R	0.93	0.94	0.97	0.93	/	0.92	/
upperbody5 R	/	0.85	0.90	0.90	0.95	/	0.93
upperbody1 L	0.95	0.90	0.97	/	/	/	/
upperbody2 L	0.96	0.90	0.88	/	/	/	/
upperbody3 L	0.72	0.95	0.74	0.92	/	0.92	/
upperbody4 L	0.73	0.80	0.94	0.93	/	0.94	/
upperbody5 L	/	0.88	0.86	0.90	0.88	/	0.87

*R denotes the right hand movement and L the left hand movement

Both upper body and arm/hand MPIs have demonstrated the high test-retest reliability (ICC parameter $\in$ [0.72-0.99]). Still, the arm/hand MPIs have shown higher test-retest reliability (ICC parameter $\in$ [0.81-0.99]) than the upper body MPIs. Table 6.6 has some empty fields in accordance to the extracted upper body MPIs per each movement (Table 6.4).

Table 6.7: Test-retest reliability for the arm/hand MPIs

	ICC reliability parameter						
Movement	ACC-SSI	ACC-RAN	GYRO-SSI	GYRO-RAN	EMG-MAV	EMG-VAR	EMG-WC
arm/hand1 R	0.94	0.95	0.81	0.91	0.94	0.86	0.94
arm/hand2 R	0.97	0.97	0.86	0.94	0.93	0.84	0.93
arm/hand3 R	0.97	0.98	0.90	0.96	0.96	0.89	0.96
arm/hand4 R	0.98	0.98	0.92	0.97	0.95	0.89	0.95
arm/hand5 R	0.98	0.99	0.95	0.98	0.96	0.90	0.96
arm/hand6 R	0.98	0.99	0.95	0.98	0.97	0.92	0.97
arm/hand1 L	0.98	0.99	0.96	0.98	0.97	0.93	0.97
arm/hand2 L	0.98	0.99	0.95	0.99	0.97	0.94	0.97
arm/hand3 L	0.98	0.99	0.94	0.98	0.98	0.94	0.98
arm/hand4 L	0.98	0.99	0.95	0.99	0.98	0.95	0.98
arm/hand5 L	0.98	0.99	0.95	0.99	0.98	0.95	0.99
arm/hand6 L	0.99	0.99	0.96	0.99	0.98	0.95	0.99

*R denotes the right hand movement and L the left hand movement

6.4.2 Healthy-affected side analysis

As discussed previously, the progress monitoring of the affected hand is the most important task in the rehabilitation after stroke. Another important concept is the performance comparison between the healthy and affected hand. The desired goal is that the affected hand performance reaches the healthy hand performance. Although this goal cannot be achieved in the most cases, the comparison is an important indicator of the affected hand advancement. In this section, we investigate whether the proposed MPIs can emphasize the differences in the movement performance with the affected and healthy hand. We address both groups of the tested movements, upper body and arm/hand movements.

In order to complete this task, the statistical comparison has been performed. The choice of statistical tests depends on the data distribution. For data with a normal distribution, the ANOVA test is the appropriate choice. Otherwise, its nonparametric equivalent, Kruskal-Wallis test (Field [2009]) has to be applied. We performed the Kolmogorov-Smirnov test to assess the normal distribution hypothesis. The test rejected the normal distribution hypothesis with a 0.05 significance level. Consequently, two-sided Wilcoxon rank sum test is applied between the MPI values obtained firom the healthy and affected hand. The corresponding MPI is considered as relevant for the healthy-affected side analysis if it satisfies the following conditions: (i) the difference between the MPI values for the healthy and affected hand is statistically significant ($p<0.05$) and (ii) the MPI values for the healthy hand are larger than the MPI values for the affected hand.

In the case of the upper body movements, there are twenty-one MPIs in total (Table 6.4). Only four upper body MPIs does not meet the statistical requirement in terms of the healthy-affected side analysis ($p > 0.05$). Those MPIs are SR for the upperbody3, upperbody4 and upperbody5 movements and MS for the upperbody5 movement. Still, the

remaining 17 MPIs turn out to be very relevant in distinguishing the performance of the healthy and affected hand, which is more than 80% of the extracted upper body MPIs.

Regarding the arm/hand movements, there are forty-two MPIs in total - seven different MPIs (Table 6.5) for six movements (Table 6.3). Results of the statistical analysis underline 37 MPIs out of 42 MPIs in total to be relevant for the healthy-affected side analysis. The non-relevant MPIs are only the EMG MPIs for the arm/hand3 movement and GYRO MPIs for the arm/hand2 movement. This result suggest that more than 88% of the extracted arm/hand MPIs provide the quantitative information about differences between the healthy and affected hand.

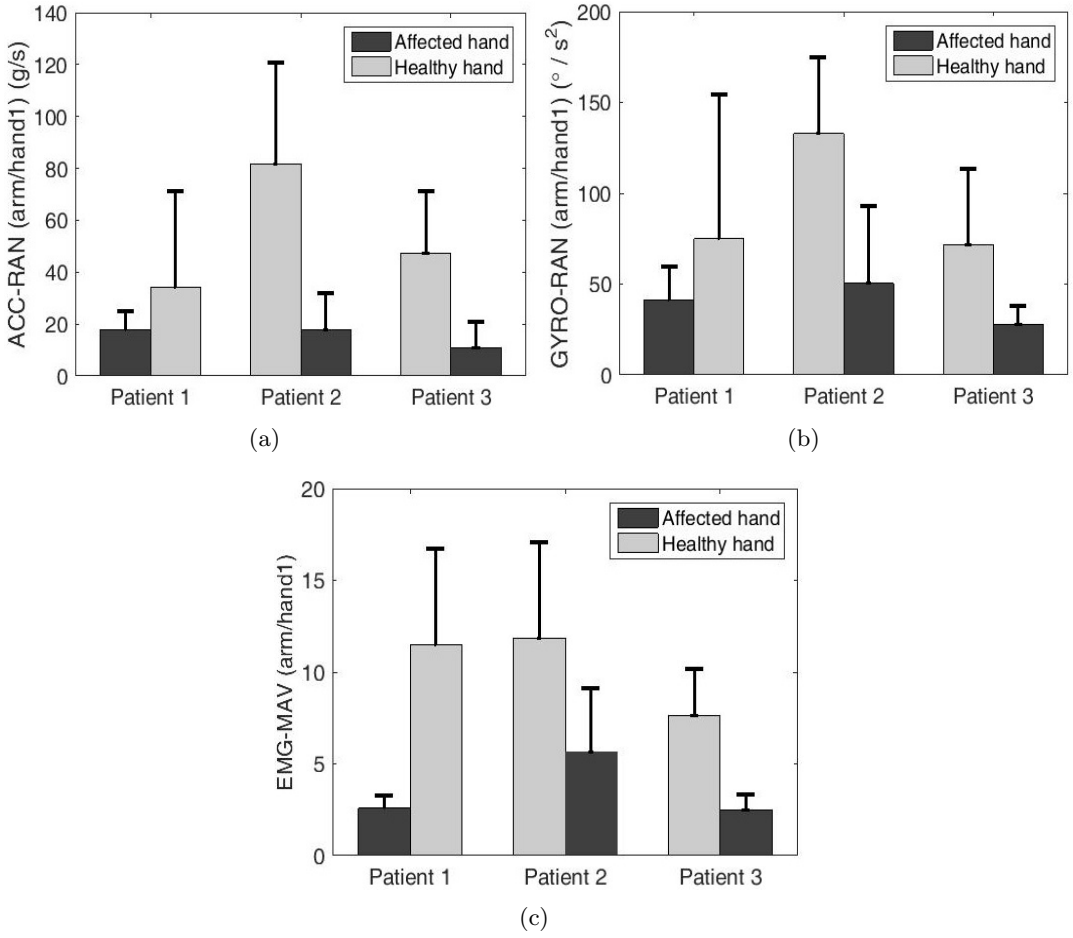


Figure 6.8: ACC-RAN (a), GYRO-RAN (b) and EMG-MAV for the affected and healthy hand (arm/hand1 movement)

Figure 6.8 presents the mean and standard deviation graph of ACC-RAN, GYRO-RAN and EMG-MAV MPI (arm/hand1 movement) for the healthy and affected hand performance. The figure clearly illustrates the larger mean MPI values for the healthy hand in comparison to the affected hand. Such outcome is expected, since the affected hand

has lower movement performance.

The overall conclusion is that the arm/hand MPIs are more relevant for the healthy-affected side analysis than the upper body MPIs. The arm/hand movements give better insight into the patient state after stroke since they particularly employ the affected hand. On the other side, the upper body movements are more general, but still, provide the information about the movement performance with an affected hand. In addition, MPIs extracted from the arm/hand movements are more informative since they are obtained in the vector form (the temporal evolution of the values calculated inside the sliding windows, using the window approach (Section 5.3)).

6.4.3 Correlations with clinical scale

In this section, we investigate whether the proposed MPIs evaluate the patients' movement performance in the same manner as the official clinical scale [Fugl-Meyer et al., 1974] for the monitoring of the stroke patients. This task is particularly important for the possible inclusion of the proposed MPIs into medical protocols. We have addressed both, upper body and arm/hand MPIs, proposed earlier in this chapter.

The values of the Fugl-Meyer scale are obtained as a result of a physiatrist's evaluation right before the sensor measurements. Correlations were calculated using Pearson's correlation coefficient r (takes values between -1 and 0 for negative correlation and between 0 and 1 for positive correlation), along with the p-value and confidence intervals. Values of r closer to -1 in the case negative correlation and closer to 1 in the case of positive correlation indicate a better correlation between the variables.

The correlations between the upper body MPIs and Fugl-Meyer clinical scale are presented in Table 6.8. The presented results are obtained based on the joint MPI data for all three patients, taking into account only the affected hand, since the Fugl-Meyer scale evaluate the performance of the affected hand during the recovery. MPIs related to the range of motion (ROM), the speed of the movement (MS) and angle measurements (MSA) have a positive correlation with the clinical scale, since the higher values of these MPIs indicate the better performance of the patients, as well as the higher values of the clinical scale.

Table 6.8: Correlation between the upper body MPIs and Fugl-Meyer clinical scale

	Pearson's correlation coefficient r						
Movement	ROM shoulder	MS	SR	VDBH	VSED	ROM elbow	MSA
upperbody1	0.67	0.61	-0.97	/	/	/	/
upperbody2	0.72	0.78	-0.79	/	/	/	/
upperbody3	0.74	0.75	-0.68	-0.90	/	0.69	/
upperbody4	0.98	0.54	-0.90	-0.90	/	0.96	/
upperbody5	/	0.80	-0.69	-0.96	-0.80	/	0.92

On the other side, MPIs related to the differences between hands (VDBH) and be-

tween the shoulder and elbow (VSED) in the final movement position have a negative correlation with the clinical scale, since the lower values of these MPIs suggest better patients' performance. Finally, in the case of SR MPI, we take into account the absolute difference of the obtained SR MPI value and 1 (the value of SR for proper movements). Hence, the smaller differences indicate the better movement performance and consequently, the SR MPI has a negative correlation with the clinical scale, as well. The obtained absolute values of the Pearson's correlation coefficient r across all MPIs and tested movements are inside the range [0.54 - 0.98] (Table 6.8). MPIs that have demonstrated the very high correlation with the clinical scale ($0.80 < r < 1$) are VDBH, VSED, MSA, as well as the remaining four MPIs, but only for particular movements.

Table 6.9 present the correlations between the arm/hand MPIs and Fugl-Meyer clinical scale, based on the Pearson's correlation coefficient r. All MPIs have a positive correlation with the clinical scale, since the higher values of all MPIs indicate the better performance of the patients, as well as the higher values of the clinical scale. The correlation of the arm/hand MPIs with the Fugl-Meyer clinical scale is slightly weaker than in the case of upper body MPIs. This can be a consequence of the averaging the arm/hand MPIs. In fact, their values are obtained using the window approach and the movement is described based on the array of the MPIs calculated inside the sliding windows. On the other side, the value of the clinical scale represent only one number and consequently, the arm/hand MPIs need to be reduced to one number in order to perform the correlation analysis. In such cases, the mean value is imposed as the relevant estimator, but the loss of the information is the side effect. Even if the correlation with the clinical scale is not high, the arm/hand MPIs still represent valuable descriptors, since they give the insight about the MPI values along the time during the movement performance. Consequently, they are more informative than the clinical scale, considering that the clinical scale reduces the entire movement performance to one number. The correlation analysis emphasize the MPIs extracted from the arm/hand5 and arm/hand6 movements to be the most correlated with Fugl-Meyer scale (Table 6.9). Those movements refers to the object grasping, pick and place in the case of easy and heavy load.

Table 6.9: Correlation between the arm/hand MPIs and Fugl-Meyer clinical scale

	Pearson's correlation coefficient r						
Movement	ACC-SSI	ACC-RAN	GYRO-SSI	GYRO-RAN	EMG-MAV	EMG-VAR	EMG-WC
arm/hand1	0.55	0.68	0.76	0.73	0.54	0.47	0.52
arm/hand2	0.86	0.80	0.58	0.71	0.65	0.65	0.64
arm/hand3	0.60	0.65	0.65	0.72	0.88	0.70	0.88
arm/hand4	0.60	0.65	0.65	0.72	0.51	0.50	0.52
arm/hand5	0.73	0.82	0.83	0.87	0.75	0.71	0.76
arm/hand6	0.71	0.67	0.77	0.80	0.73	0.70	0.72

6.4.4 GUI application for storing, visualization and interpretation of the sensor data and MPIs with design of the personal patients' profiles

In the previous three chapters related to the movement quantification in Parkinson's disease (Chapters 3, 4, 5), the patients were analyzed by groups (patients vs. controls and disease stage groups). The main outcome of the movement performance analysis was the affiliation to a particular group in order to support the clinical evaluations (disease diagnosis and progress monitoring). The main reason for this approach is the fact that in Parkinson's disease, patients' condition change very slow. The period between the significant changes in the movement performance is usually one to two years.

On the other side, after the stroke occurrence, the patients' recovery can be fast in the case of the appropriate rehabilitation therapy. The period between the significant changes in the movement performance is approximately one to two weeks, if the rehabilitation session is practiced every day. Consequently, the approach to the quantification of the movement performance after the stroke is patient-oriented. This means that the patients are monitored and analyzed individually and the reports about their performance over time are provided to medical domain experts to support their clinical evaluations.

We develop a software application for storing, visualization and interpretation of the collected sensor data and calculated movement measurements (MPIs). The application is intended to support the clinical evaluations by medical doctors and to store the patients' data over time. Based on the obtained movement scores (MPIs), we build the personal profile for each patient that gives insight into the movement performance over time.

The application part related to the upper body movements information consists of the following units:

- List of the patients, along with the relevant clinical data (Figure 6.9(a)), such as stroke type, the time of the stroke occurrence, which hand is affected by the stroke, etc.
- List of the acquired movements (Figure 6.9(b));
- Visualization of the collected skeleton joints during the movement performance for each rehabilitation session (Figure 6.9(c));
- List of the MPIs calculated from the movements (Figure 6.9(d)), along with the graphical representation of their values across sessions (Figure 6.9(e)).

The application part related to the arm/hand movements information is built in the same manner and conceptually, it contains the same application units as in the case of the upper body movements. The difference is in the data content: sensor outputs, collected movements and extracted MPIs.

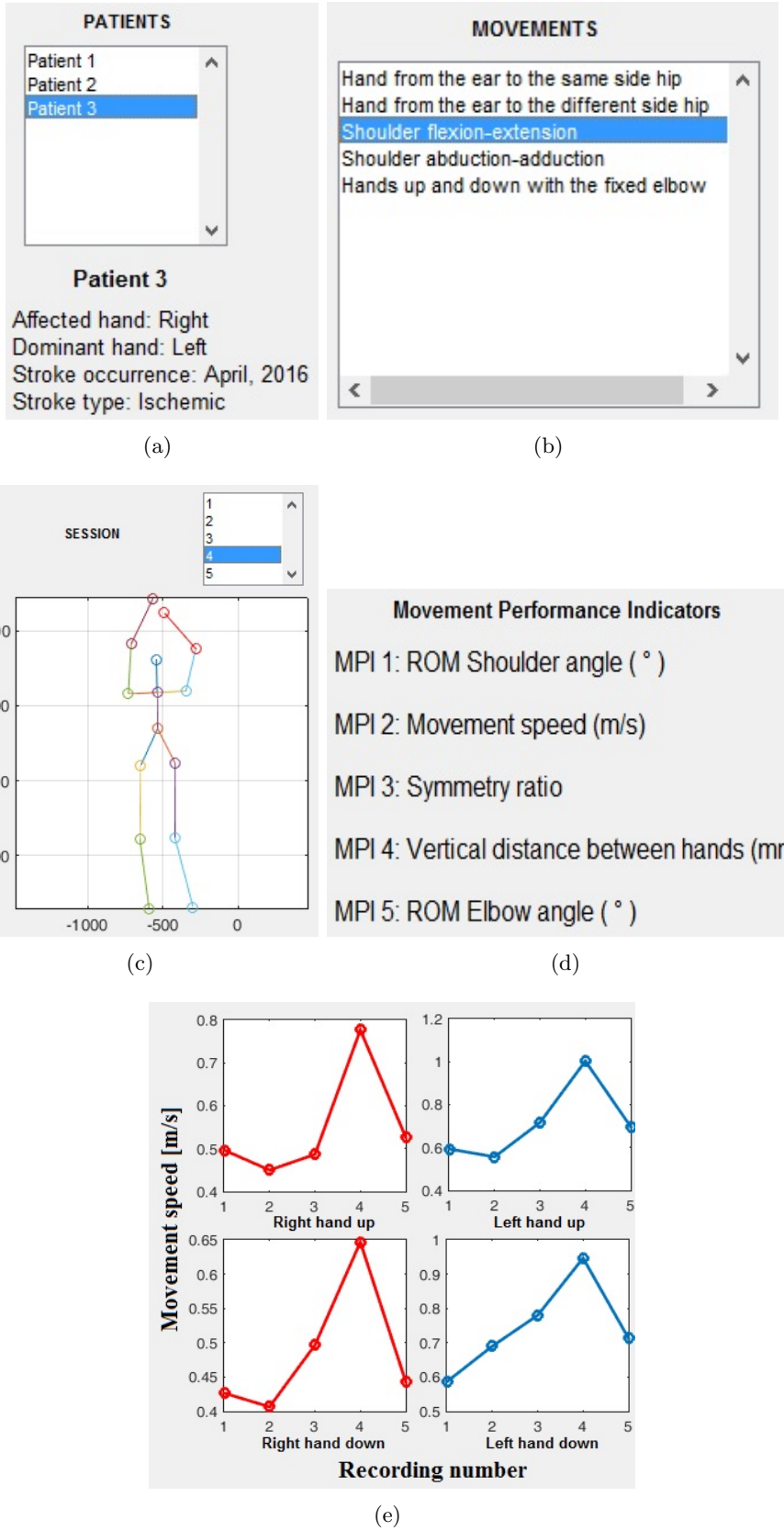


Figure 6.9: Application units (upper body movements): list of the patients, along with the relevant clinical data (a), list of the acquired movements (b), collected skeleton joints during the movement performance for each rehabilitation session (c), MPIs extracted from the movements (d) and evolution of the MS MPI for the shoulder abduction-adduction movement (upperbody4) across five recordings (e)

6.5 Summary and discussion

In this chapter, we have presented an approach for quantitative movement analysis, based on the upper body movement data collected using the Kinect device and arm/hand movement data acquired with an armband EMG sensor. Experimental group consists of patients recovering from the stroke and the tested movements employ both, affected and healthy arm. Our results show that the proposed approach has the potential to be adopted by physiatrists, to enhance objectivity and precision, during the progress monitoring evaluations. At the same time, it opens the possibility of low-cost home rehabilitation.

We propose a set of 21 MPIs to characterize the upper body movements and a set of 42 MPIs to quantify the arm/hand movements. We conducted a thorough analysis of the properties of these MPIs, to identify their importance in terms of the technical and stroke-related clinical aspects: (i) statistical analysis of the repeated sensor measurements, (ii) healthy-affected side analysis, (iii) correlation with clinical (Fugl-Meyer) scale and (iv) design of an application for storing, visualization and interpretation of the sensor data and MPIs including the personal patients' profiles.

Statistical analysis of the repeated sensor measurements confirmed the internal consistency of the sensor measurements (both Kinect and armband device), as well as the high test-retest reliability of the extracted MPIs (Section 6.4.1). The results of the healthy-affected side analysis report the high percentage of the MPIs relevant for assessing the differences between the healthy and affected hand - more than 80% for upper body MPIs (17 out of 21 in total) and more than 88% in the case of arm/hand MPIs (37 out of 42) (Section 6.4.2). The correlation analysis emphasizes the good correlation between the upper body MPIs and clinical (Fugl-Meyer) scale (Table 6.8). On the other side, the correlation with the clinical scale regarding the arm/hand MPIs is slightly weaker than in the case of upper body MPIs. Still, MPIs extracted from the arm/hand5 and arm/hand6 movements demonstrate quite high correlation with Fugl-Meyer scale (Table 6.9). Furthermore, the temporal evolution of the arm/hand MPIs can be even more informative than the clinical scale, considering that the clinical scale reduces the entire movement performance to one number.

Finally, we have designed an application for storing, visualization and interpretation of the clinical data, as well as raw and processed sensor data (extracted MPIs). The application is intended to support the post-stroke clinical evaluations by medical doctors and to store the patients' data over time. Based on the collected clinical and sensor data, the personal profile is built for each patient giving the insight into the movement performance during the recovery process. Using the application, the physiatrists can have the unified evidence about patients' progress. On the other side, the application can be used by patients in the home rehabilitation, as well.

Chapter 7

Conclusions and future work

In this chapter, we make a summary of the thesis contributions and propose the future extensions of this dissertation.

7.1 Thesis contributions

In this thesis, we develop three different approaches for movement quantification in Parkinson's disease and a method for movement assessment in patients recovering from the stroke. The aim is to support clinical evaluations in disease diagnosis and progress monitoring relying on the objective approach i.e. designed Movement Performance Indicators (MPIs) extracted from the sensor data. In parallel, we propose a concept of low-cost, marker-free, wearable and wireless sensor system, suitable for inclusion into clinical and home rehabilitation.

First, we have presented an approach for quantitative movement analysis, based on the full-body movement data. The gait test and upper body movements are acquired using the low-cost vision-based Kinect device. Our results have shown significant differences between patients and controls for the ten MPIs extracted from the Kinect data. We propose two MPIs as novel movement measurements - the symmetry ratio SR and rigidity measure. SR demonstrated the particularly high importance for the classification procedure between patients and controls. The main limitation of the approach is that the Kinect data are not informative enough to discriminate between the disease stages. This is a consequence of the modest accuracy and precision of the Kinect readings. Additionally, full body movements give a general overview of the patient motor performance. For the particular case of PD, the analysis of the arm/hand movement behavior is necessary.

Second, the quantitative assessment of the hand movements is performed based on the sensor glove data. A set of fifteen MPIs is proposed to characterize the hand movements of subjects in the context of PD. The classification results have shown that the hand MPIs are capable to differentiate between controls and patients (diagnosis support), as

well as between different disease stages (monitoring support). This process underlined the significant role of the new MPIs we proposed: angular velocity MPIs extracted from the abduction sensor data and velocity and acceleration MPIs derived from the hand model, accompanying with the finger joint's range of motion. Additionally, the majority of the hand MPIs demonstrated the good correlation with the clinical test and scale for possible inclusion in the medical protocols. ROM of the proximal finger joints and velocity and acceleration parameters are strongly correlated with both tested clinical scales. The same group of MPIs illustrated the capability to keep track of the patients' movement performance over time in the same manner as the clinical measurements.
The data glove sensor has proven to be more informative than the Kinect for assessing the PD main symptoms and the disease stages. This is due to the higher importance of the fine hand movement analysis, particularly for PD evaluations in comparison to the full-body movements. However, due to its high cost, the data glove device has been used as the proof of concept and the final version of the rehabilitation system will contain alternative low-cost data glove or another suitable device.
Furthermore, in the third part of the thesis, we concentrate on the arm/hand movement quantification using EMG armband device. The developed approach for quantitative movement analysis results in a set of seven basic MPIs and 84 MPIs in total across all collected movements. Extracted MPIs are further examined in terms of relevant clinical aspects: (i) reliability; (ii) classification between patients and controls and between disease stages (support to diagnosis and monitoring, respectively); (iii) left-right side analysis between controls and patients, as well as between disease stage groups and (iv) correlation with clinical scales (tapping test and UPDRS-III). The overall conclusion is that GYRO MPIs are relevant according to all clinically-relevant criterions. Particular EMG MPIs are important for the classification aspect and left-right side analysis, while the ACC MPIs are of interest for the left-right side analysis and correlation with clinical scales.
Based on the EMG data, we identify that external forearm muscles at patients have shown the lowest muscle activity in a comparison with a control group. Such result still requires clinical verification. Lastly, we conclude that sensor data collected from the wireless armband device successfully addressed the same set of relevant aspects in PD like the sensor glove data. Even more, the important aspect of the left-right side analysis is performed based on the armband sensor readings, which is not feasible with the sensor glove data, due to its right-hand design. Consequently, our results suggest that the wireless armband sensor can be a possible alternative for high-cost data glove.
Finally, in the last part of the thesis, we deal with the progress monitoring of the stroke patients using the Kinect and armband device sensor data. We propose a set of 21 MPIs to characterize the upper body movements and a set of 42 MPIs to quantify the arm/hand movements. Statistical analysis of the repeated sensor measurements confirmed the internal consistency of the sensor measurements (both Kinect and armband

device), as well as the high test-retest reliability of the extracted MPIs. The results of the healthy-affected side analysis report the high percentage of the MPIs relevant for assessing the differences between the healthy and affected hand - more than 80% for upper body MPIs (17 out of 21 in total) and more than 88% in the case of arm/hand MPIs (37 out of 42). Furthermore, we design an application for storing, visualization and interpretation of the clinical and sensor data over time. The personal patient profiles are built inside the application to facilitate the progress monitoring to medical doctors. As such, the physiatrists can have the unified evidence about patients' progress. The application can be used by patients in the home rehabilitation, as well.

7.2 Future work

The future work regarding this thesis will address following aspects:

Repeated experiments with EMG armband sensor for Parkinson's patients - We have presented the results of the repeated experiments with Kinect and data glove in order to investigate whether the sensor data can keep track of the patients' movement performance in the same way as the clinical scales. The sensor measurements were repeated after one to two and a half years from the initial measurements. The period between the experiments is conditioned by slow disease progress. Kinect data have not demonstrated the capability to support clinical evaluations during the PD progress. On the other side, sensor glove data (in the context of the particular hand MPIs) have illustrated the possibility of monitoring the patient state in the same way as clinical measurements. The same aspect of the repeated measurements analysis will be conducted for EMG armband sensor data since the experiments were carried out the latest. Consequently, the required period for the repeated measurements has not passed yet.

Expanding the experimental set for stroke patients - Our method for movement quantification in the post-stroke period is validated based on the data for three different patients, whereby the sensor measurements for each patient were repeated five times. The next step will be the extension of the data set towards final verification of the proposed approach.

MPIs extraction from the frequency domain - In this thesis, our focus is on the MPIs that are extracted from the sensor signals' time domain. Regarding the armband sensor data in Parkinson's patients, the frequency domain MPIs based on the Teager energy are initially extracted from EMG and IMU readings. However, the reliability of those MPIs was poor and consequently, they are excluded from the further analysis. Still, there are a lot of different possibilities for extracting the frequency domain MPIs from the sensor signals. This task will represent the next step in the design of new MPIs.

Quantification of the balance and stability in PD - Until now, we have addressed

gait, upper body, arm/hand and fine hand movements of Parkinson's patients. The only remaining aspect worth to investigate in PD is the balance and postural stability since the patients often experience difficulties in maintaining the balance. We are considering using a low-cost device with sensors of pressure for balance quantification.

Bibliography

Gyberglove. http://www.cyberglovesystems.com/products/cyberglove-II/overview.

Myoarmband. https://www.myo.com/.

Roboticstoolbox. http://petercorke.com/Robotics_Toolbox.html.

João Gabriel Abreu, João Marcelo Teixeira, Lucas Silva Figueiredo, and Veronica Teichrieb. Evaluating sign language recognition using the myo armband. In *Virtual and Augmented Reality (SVR), 2016 XVIII Symposium on*, pages 64–70. IEEE, 2016.

S. Albiol-Perez, J. Lozano-Quilis, H. Gil-Gomez, and et al. Virtual rehabilitation system for people with parkinson's disease. In *Proceedings of the 9th international conference on disability, virtual reality and associated technologies (ICDVRAT)*, pages 423–426, 2012.

J. Alon, V. Athitsos, and Sclaroff S. Accurate and efficient gesture spotting via pruning and subgesture reasoning. In *Proceedings of the International Workshop on Human-Computer Interaction*, pages 189–198, 2005.

D. Anton, A. Goni, and A. Illarramendi. Exercise recognition for kinect-based telerehabilitation. *Methods Inf Med*, 54(2):145–155, 2015.

Z. Arief, Sulistijono IA., and RA. Ardiansyah. Comparison of five time series emg features extractions using myo armband. In *Proceedings of the IEEE International Electronics Symposium (IES)*, pages 11–14, 2015.

Roland N Auer and Garnette R Sutherland. Primary intracerebral hemorrhage: pathophysiology. *The Canadian journal of neurological sciences. Le journal canadien des sciences neurologiques*, 32:S3–12, 2005.

M Bächlin, M Plotnik, D Roggen, N Giladi, JM Hausdorff, and G Tröster. A wearable system to assist walking of parkinson s disease patients. *Methods of information in medicine*, 49(1):88, 2010.

Xiao Bao, Yurong Mao, Qiang Lin, Yunhai Qiu, Shaozhen Chen, Le Li, Ryan S Cates, Shufeng Zhou, and Dongfeng Huang. Mechanism of kinect-based virtual reality training for motor functional recovery of upper limbs after subacute stroke. *Neural regeneration research*, 8(31):2904, 2013.

Kirsty Bhattacharya, Daniela Saadia, Barbara Eisenkraft, Melvin Yahr, Warren Olanow, Burton Drayer, and Horacio Kaufmann. Brain magnetic resonance imaging in multiple-system atrophy and parkinson disease: a diagnostic algorithm. *Archives of Neurology*, 59(5):835–842, 2002.

Berta Bobath. *Adult hemiplegia: evaluation and treatment*. Elsevier Health Sciences, 1990.

Reza Boostani and Mohammad Hassan Moradi. Evaluation of the forearm emg signal features for the control of a prosthetic hand. *Physiological measurement*, 24(2):309, 2003.

Ali Boyali, Naohisa Hashimoto, and Osamu Matsumoto. Hand posture and gesture recognition using myo armband and spectral collaborative representation based classification. In *Consumer Electronics (GCCE), 2015 IEEE 4th Global Conference on*, pages 200–201. IEEE, 2015.

Heiko Braak, Kelly Del Tredici, Hansjürgen Bratzke, John Hamm-Clement, Daniele Sandmann-Keil, and Udo Rüb. Staging of the intracerebral inclusion body pathology associated with idiopathic parkinson's disease (preclinical and clinical stages). *Journal of neurology*, 249:III–1, 2002.

Jurgen Broeren, Lisbeth Claesson, Daniel Goude, Martin Rydmark, and Katharina S Sunnerhagen. Virtual rehabilitation in an activity centre for community-dwelling persons with stroke. *Cerebrovascular Diseases*, 26(3):289–296, 2008.

D. Bullock and S. Grossberg. Adaptive neural networks for control of movement trajectories invariant under speed and force rescaling. *Hum Mov Sci*, 10(1):3–53, 1991.

A. Calin, A. Cantea, A. Dascalu, and et al. Mira – upper limb rehabilitation system using microsoft kinect. *Studia Universitatis Babes-Bolyai, Informatica*, 56(4):63–74, 2011.

Sarvenaz Chaeibakhsh, Elissa Phillips, Amanda Buchanan, and Eric Wade. Upper extremity post-stroke motion quality estimation with decision trees and bagging forests. In *Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the*, pages 4585–4588. IEEE, 2016.

C. Chang, B. Lange, M. Zhang, and et al. Towards pervasive physical rehabilitation using microsoft kinect. In *Proceedings of the 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth)*, pages 159–162, 2012.

Y. Chang, S. Chen, and J. Huang. A kinect-based system for physical rehabilitation: A pilot study for young adults with motor disabilities. *Res Dev Disabil*, 32(6): 2566–2570, 2011.

Y Chang, W. Han, and Y. Tsai. A kinect-based upper limb rehabilitation system to assist people with cerebral palsy. *Res Dev Disabil*, 34(11):3654–3659, 2013.

Binith Cheeran, Leonardo Cohen, Bruce Dobkin, Gary Ford, Richard Greenwood, David Howard, Masud Husain, Malcolm Macleod, Randolph Nudo, John Rothwell, et al. The future of restorative neurosciences in stroke: driving the translational research pipeline from basic science to rehabilitation of people after stroke. *Neurorehabilitation and neural repair*, 23(2):97–107, 2009.

F. Chen, C. Fu, and C. Huang. Hand gesture recognition using a real-time tracking method and hidden markov models. *Image and Video Computing*, 21(8):745–758, 2003.

CW. Cho, WH. Chao, SH. Lin, and et al. A vision-based analysis system for gait recognition in patients with parkinson's disease. *Expert Syst Appl*, 36(3):7033–7039, 2009.

R. Clark, Y. Pu, K. Fortina, and et al. Validity of the microsoft kinect for assessment of postural control. *Gait and Posture*, 36(3):372–377, 2012.

Gustavo Costa, JA Abin-Carriquiry, and Federico Dajas. Nicotine prevents striatal dopamine loss produced by 6-hydroxydopamine lesion in the substantia nigra. *Brain research*, 888(2):336–342, 2001.

Houde Dai, Haijun Lin, and Tim C Lueth. Quantitative assessment of parkinsonian bradykinesia based on an inertial measurement unit. *Biomedical engineering online*, 14(1):68, 2015.

TJ. Darrell, IA. Essa, and Pentland AP. Task-specific gesture analysis in real-time using interpo-lated views. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 18(12):1236–1242, 1996.

G. De Michele, S. Sello, MC. Carboncini, B. Rossi, and et al. Cross-correlation time-frequency analysis for multiple emg signals in parkinson's disease: a wavelet approach. *Med Eng Phys*, 25(5):361–369, 2003.

MC d de Rijk, C Tzourio, MM Breteler, JF Dartigues, L Amaducci, S Lopez-Pousa, JM Manubens-Bertran, A Alperovitch, and Walter A Rocca. Prevalence of parkinsonism and parkinson's disease in europe: the europarkinson collaborative study. european community concerted action on the epidemiology of parkinson's disease. *Journal of Neurology, Neurosurgery & Psychiatry*, 62(1):10–15, 1997.

Mona L Delva and Carlo Menon. Inertial characteristics of upper extremity motions in upper extremity stroke rehabilitation based tasks. In *Biomedical Robotics and Biomechatronics (BioRob), 2016 6th IEEE International Conference on*, pages 870–875. IEEE, 2016.

Milica Djurić-Jovičić, Nenad S Jovičić, Agnes Roby-Brami, Mirjana B Popović, Vladimir S Kostić, and Antonije R Djordjević. Quantification of finger-tapping angle based on wearable sensors. *Sensors*, 17(2):203, 2017.

Geoffrey A Donnan, J Baron, Stephen M Davis, and Frank R Sharp. The ischemic penumbra: overview, definition, and criteria. *NEUROLOGICAL DISEASE AND THERAPY*, 93:7, 2007.

Simone Dorsch, Louise Ada, and Colleen G Canning. Emg-triggered electrical stimulation is a feasible intervention to apply to multiple arm muscles in people early after stroke, but does not improve strength and activity more than usual therapy: a randomized feasibility trial. *Clinical rehabilitation*, 28(5):482–490, 2014.

Shabnam Sadeghi Esfahlani and Tommy Thompson. Intelligent physiotherapy through procedural content generation. In *Twelfth Artificial Intelligence and Interactive Digital Entertainment Conference*, 2016.

Timothy Exell, Christopher Freeman, Katie Meadmore, Mustafa Kutlu, Eric Rogers, Ann-Marie Hughes, Emma Hallewell, and Jane Burridge. Goal orientated stroke rehabilitation utilising electrical stimulation, iterative learning and microsoft kinect. In *Rehabilitation Robotics (ICORR), 2013 IEEE International Conference on*, pages 1–6. IEEE, 2013.

Tom Fawcett. An introduction to roc analysis. *Pattern recognition letters*, 27(8): 861–874, 2006.

A. Fernandez-Baena, A. Susin, and X. Lligadas. Biomechanical validation of upper-body and lower-body joint movements of kinectmotion capture data for rehabilitation treatments. In *6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth*, pages 159–162, 2012.

A. Field. *Discovering statistics using SPSS*. Sage publications, 2009.

Marc Fisher. The ischemic penumbra: identification, evolution and treatment concepts. *Cerebrovascular diseases*, 17(Suppl. 1):1–6, 2004.

RA. Fisher. The use of multiple measurements in taxonomic problems. *Annals of Eugenics*, 7(2):179–188, 1936.

Beverley French, Lois H Thomas, Michael J Leathley, Christopher J Sutton, Joanna McAdam, Anne Forster, Peter Langhorne, Christopher IM Price, Andrew Walker, Caroline L Watkins, et al. Repetitive task training for improving functional ability after stroke. *The Cochrane Library*, 2007.

AR. Fugl-Meyer, L. Jaasko, I. Leyman, and et al. The post-stroke hemiplegic patient. 1. a method for evaluation of physical performance. *Scandinavian journal of rehabilitation medicine*, 7(1):13–31, 1974.

A Gallina, CL Pollock, TM Vieira, TD Ivanova, and SJ Garland. Between-day reliability of triceps surae responses to standing perturbations in people post-stroke and healthy controls: A high-density surface emg investigation. *Gait & posture*, 44: 103–109, 2016.

B. Galna, G. Barry, D. Jackson, and et al. Accuracy of the microsoft kinect sensor for measuring movement in people with parkinson's disease. *Gait and Posture*, 39(4): 1062–1068, 2014a.

B. Galna, D. Jackson, G. Schofield, and et al. Retraining function in people with parkinson's disease using the microsoft kinect: game design and pilot testing. *J Neuroeng Rehabil*, 11(60):1–15, 2014b.

A. Gama, T. Chaves, L. Figueiredo, and et al. Guidance and movement correction based on therapeutics movements for motor rehabilitation support systems. In *Proceedings of the 14th Symposium on Virtual and Augmented Reality (SVR)*, pages 191–200. IEEE, 2012.

Asilbek Ganiev, Ho-Sun Shin, and Kang-Hee Lee. Study on virtual control of a robotic arm via a myo armband for the selfmanipulation of a hand amputee. *Int. J. Appl. Eng. Res*, 11(2):775–782, 2016.

MI Garry, A Loftus, and JJ Summers. Mirror, mirror on the wall: viewing a mirror reflection of unilateral hand movements facilitates ipsilateral m1 excitability. *Experimental Brain Research*, 163(1):118–122, 2005.

Nooshin Haji Ghassemi, Franz Marxreiter, Cristian F Pasluosta, Patrick Kugler, Johannes Schlachetzki, Axel Schramm, Bjoern M Eskofier, and Jochen Klucken. Combined accelerometer and emg analysis to differentiate essential tremor from parkin-

son's disease. In *Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the*, pages 672–675. IEEE, 2016.

C. Goetz, W. Poewe, O. Rasco, and et al. Movement disorder society task force report on the hoehn and yahr staging scale: Status and recommendations. *Mov Disord*, 19 (9):1020–1028, 2004.

C. Goetz, B. Tilley, S. Shaftman, and et al. Movement disorder society-sponsored revision of the unified parkinson's disease rating scale (mds-updrs): Scale presentation and clinimetric testing results. *Mov Disord*, 23(15):2129–2170, 2008.

AR. Goncalves, ER. Gouveia, MS. Cameirao, and et al. Automating senior fitness testing through gesture detection with depth sensors. In *Proceedings of the IET International Conference on Technologies for Active and Assisted Living (TechAAL)*, pages 1–6, 2015.

H. Gonzalez-Jorge, B. Riveiro, E. Vazquez-Fernandez, and et al. Metrological evaluation of microsoft kinect and asus xtion sensors. *Measurement*, 46(6):1800–1806, 2013.

P. Gribble and D. Ostry. Origins of the power law relations between movement velocity and curvature: Modeling the effects of muscle mechanics and limb dynamics. *J Neurophysiol*, 76(5):2853–2860, 1996.

Achmad Alfian Hidayat, Zainal Arief, and Dedid Cahya Happyanto. Lovett scaling with flex sensor and myo armband for monitoring finger muscles therapy of post-stroke people. *EMITTER International Journal of Engineering Technology*, 3(2), 2016.

Margaret M Hoehn and Melvin D Yahr. Parkinsonism onset, progression, and mortality. *Neurology*, 17(5):427–427, 1967.

Maureen K Holden. Virtual environments for motor rehabilitation: review. *Cyberpsychology & behavior*, 8(3):187–211, 2005.

Dominic Holmes, DK Charles, PJ Morrow, S McClean, and SM McDonough. Usability and performance of leap motion and oculus rift for upper arm virtual reality stroke rehabilitation. In *Proceedings of the 11th International Conference on Disability, Virtual Reality & Associated Technologies*. Central Archive at the University of Reading, 2016.

Hossein Mousavi Hondori, Maryam Khademi, and Cristina V Lopes. Monitoring intake gestures using sensor fusion (microsoft kinect and inertial sensors) for smart home tele-rehab setting. In *2012 1st Annual IEEE Healthcare Innovation Conference*, 2012.

HP. Huang, YH. Liu, and CS. Wong. Automatic emg feature evaluation for controlling a prosthetic hand using supervised feature mining method: an intelligent approach. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, pages 220–225, 2013.

Andrew J Hughes, Susan E Daniel, Linda Kilford, and Andrew J Lees. Accuracy of clinical diagnosis of idiopathic parkinson's disease: a clinico-pathological study of 100 cases. *Journal of Neurology, Neurosurgery & Psychiatry*, 55(3):181–184, 1992.

Andrew J Hughes, Susan E Daniel, Yoav Ben-Shlomo, and Andrew J Lees. The accuracy of diagnosis of parkinsonian syndromes in a specialist movement disorder service. *Brain*, 125(4):861–870, 2002.

RP. Iacono, RR. Lonser, and G. et al. Maeda. Chronic anterior pallidal stimulation for parkinson's disease. *Acta Neurochir*, 137(1–2):106–112, 1995.

J. Jankovic. Parkinson's disease: clinical features and diagnosis. *J Neurol, Neurosurgery and Psychiatry*, 79(4):368–376, 2008.

Robert H Jebsen, NEAL Taylor, RB Trieschmann, Martha J Trotter, and Linda A Howard. An objective and standardized test of hand function. *Archives of physical medicine and rehabilitation*, 50(6):311–319, 1969.

K. Kahol, P. Tripathi, and S. Panchanathan. Automated gesture segmentation from dance sequences. In *Proceedings of the 6th IEEE International Conference on Automatic Face and Gesture Recognition*, pages 883–883, 2004.

A. Kandori, M. Yokoe, and Sakoda S. Quantitative magnetic detection of finger movements in patients with parkinson's disease. *Neurosci Res*, 49(2):253–260, 2004.

Regina Katzenschlager and Andrew J Lees. Olfaction and parkinson's syndromes: its role in differential diagnosis. *Current opinion in neurology*, 17(4):417–423, 2004.

S. Keus, B. Bloem, E. Hendriks, and et al. Evidence-based analysis of physical therapy in parkinson's disease with recommendations for practice and research. *Mov Disord*, 22(4):451–460, 2007.

K. Khoshelham and S. Elberink. Accuracy and resolution of kinect depth data for indoor mapping applications. *Sensors*, 12(2):1437–1454, 2012.

Ji-Won Kim, Jae-Ho Lee, Yuri Kwon, Chul-Seung Kim, Gwang-Moon Eom, Seong-Beom Koh, Do-Young Kwon, and Kun-Woo Park. Quantification of bradykinesia during clinical finger taps using a gyrosensor in patients with parkinson's disease. *Medical & biological engineering & computing*, 49(3):365–371, 2011.

J. Kocian, A. Girard, B. Banko, and et al. Dynamic system identification with gaussian processes. *Mathematical and Computer Modelling of Dynamical Systems*, 11(4):411–424, 2005.

DY. Kwon. *A Design Framework for 3D Spatial Gesture Interfaces*. PhD thesis, ETH, Switzerland, 2008.

Anthony E Lang, Terry Curran, John Provias, and Catherine Bergeron. Striatonigral degeneration: iron deposition in putamen correlates with the slit-like void signal of magnetic resonance imaging. *Canadian Journal of Neurological Sciences/Journal Canadien des Sciences Neurologiques*, 21(04):311–318, 1994.

B. Lange, S. Koenig, E. McConnell, and et al. Interactive game-based rehabilitation using the microsoft kinect. In *Proceedings of the IEEE Virtual Reality Short Papers and Posters (VRW)*, pages 171–172, 2012.

Peter Langhorne, Fiona Coupar, and Alex Pollock. Motor recovery after stroke: a systematic review. *The Lancet Neurology*, 8(8):741–754, 2009.

Annemarie Laudanski, Brenda Brouwer, and Qingguo Li. Activity classification in persons with stroke based on frequency features. *Medical engineering & physics*, 37 (2):180–186, 2015.

David E Lilienfeld and Daniel P Perl. Projected neurodegenerative disease mortality in the united states, 1990–2040. *Neuroepidemiology*, 12(4):219–228, 1993.

R. Lipovsky and HA. Ferreira. Hand therapist: A rehabilitation approach based on wearable technology and video gaming. In *Proceedings of the 4th Portuguese Meeting on Bioengineering (ENBENG)*, pages 1–2, 2015.

Rastislav Lipovskỳ and Hugo Alexandre Ferreira. Self hand-rehabilitation system based on wearable technology. In *Proceedings of the 3rd 2015 Workshop on ICTs for improving Patients Rehabilitation Research Techniques*, pages 93–95. ACM, 2015.

Zhenqiang Liu, Wennan Chang, Shili Sheng, Liang Li, Yew Guan Soo, Che Fai Yeong, Masato Odagaki, and Feng Duan. A novel upper limb training system based on ur5 using semg and imu sensors. In *Robotics and Biomimetics (ROBIO), 2016 IEEE International Conference on*, pages 1069–1074. IEEE, 2016.

Rafael Lozano, Mohsen Naghavi, Kyle Foreman, Stephen Lim, Kenji Shibuya, Victor Aboyans, Jerry Abraham, Timothy Adair, Rakesh Aggarwal, Stephanie Y Ahn, et al. Global and regional mortality from 235 causes of death for 20 age groups in 1990 and 2010: a systematic analysis for the global burden of disease study 2010. *The Lancet*, 380(9859):2095–2128, 2013.

P. Lum, C. Burgar, P. Shor, and et al. Robot-assisted movement training compared with conventional therapy techniques for the rehabilitation of upper-limb motor function after stroke. *Arch Phys Med Rehabil*, 83(7):952–959, 2002.

W. Maetzler, J. Domingos, K. Srulijes, and et al. Quantitative wearable sensors for objective assessment of parkinson's disease. *Mov Disord*, 28(12):1628–1637, 2013.

AI. Meigal, S. Rissanen, MP. Tarvainen, and et al. Novel parameters of surface emg in patients with parkinson's disease and healthy young and old controls. *J Electromyogr Kinesiol*, 19(3):e206–e213, 2009.

D. Mirkov, S. Milanovic, D. Ilic, and et al. Symmetry of discrete and oscillatory elbow movements: Does it depend on torque that the agonist and antagonist muscle can exert? *Motor control*, 6(3):271–281, 2002.

S. Mithileysh and R. Sharanya. Myo armband for physiotherapy healthcare: A case study using gesture recognition application. In *Proceedings of the 8th International Conference on Communication Systems and Networks (COMSNETS)*, pages 1–6, 2016.

Chihiro Mizuike, Shohei Ohgi, and Satoru Morita. Analysis of stroke patient walking dynamics using a tri-axial accelerometer. *Gait & posture*, 30(1):60–64, 2009.

DM Morens, A Grandinetti, D Reed, LR White, and GW Ross. Cigarette smoking and protection from parkinson's disease false association or etiologic clue? *Neurology*, 45(6):1041–1051, 1995.

DM Morens, JW Davis, A Grandinetti, GW Ross, JS Popper, and LR White. Epidemiologic observations on parkinson's disease incidence and mortality in a prospective study of middle-aged men. *Neurology*, 46(4):1044–1050, 1996.

C. Morrow, K. Docan and G. et al. Burdea. Low-cost virtual rehabilitation of the hand for patients post-stroke. In *Proceedings of the International IEEE Workshop on Virtual Rehabilitation*, pages 6–10, 2006.

Emi Narai, Hiroshi Hagino, Taiki Komatsu, and Fumiharu Togo. Accelerometer-based monitoring of upper limb movement in older adults with acute and subacute stroke. *Journal of Geriatric Physical Therapy*, 39(4):171–177, 2016.

B. Nery and R. Ventura. A dynamical systems approach to online event segmentation in cognitive robotics. *Journal of Behavioral Robotics*, 2(1):18–24, 2011.

B. Nery and R. Ventura. On the scalability and convergence of simultaneous parameter identification and synchronization of dynamical systems. *Complex Systems*, 22(3): 203–219, 2013.

K. Niazmand, K. Tonn, A Kalaras, and et al. Quantitative evaluation of parkinson's disease using sensor based smart glove. In *Proceedings of the 24th International Symposium on Computer-Based Medical Systems (CBMS)*, pages 1–8, 2011.

Alice Nieuwboer, René Dom, Willy De Weerdt, Kaat Desloovere, Luc Janssens, and Vangheluwe Stijn. Electromyographic profiles of gait prior to onset of freezing episodes in patients with parkinson's disease. *Brain*, 127(7):1650–1660, 2004.

Marika Noorkõiv, Helen Rodgers, and Christopher I Price. Accelerometer measurement of upper extremity movement after stroke: a systematic review of clinical studies. *Journal of neuroengineering and rehabilitation*, 11(1):144, 2014.

Roberto Oboe, Alessandro Tonin, Koyo Yu, Kouhei Ohnishi, and Andrea Turolla. Robotic finger rehabilitation system for stroke patient using surface emg armband. In *Industrial Electronics Society, IECON 2016-42nd Annual Conference of the IEEE*, pages 785–790. IEEE, 2016.

R. Oka. Spotting method for classification of real world data. *The Computer Journal*, 3(8):559–565, 1998.

R. Okuno, M. Yokoe, K. Akazawa, and et al. Finger taps movement acceleration measurement system for quantitative diagnosis of parkinson's disease. In *Proceedings of the 28th Annual International Conference of the Engineering in Medicine and Biology Society (EMBS)*, pages 6623–6626, 2006.

R. Okuno, M. Yokoe, K. Fukawa, and et al. Measurement system of finger-tapping contact force for quantitative diagnosis of parkinson's disease. In *Proceedings of the 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS)*, pages 1354–1357, 2007.

C Warren Olanow and William C Koller. An algorithm (decision tree) for the management of parkinson's disease treatment guidelines. *Neurology*, 50(3 Suppl 3):S1–S1, 1998.

C Warren Olanow, Ray L Watts, and William C Koller. An algorithm (decision tree) for the management of parkinson's disease (2001): treatment guidelines. *Neurology*, 56(suppl 5):S1–S88, 2001.

F. Parisi, G. Ferrari, M. Giuberti, and et al. Body-sensor-network-based kinematic characterization and comparative outlook of updrs scoring in leg agility, sit-to-stand, and gait tasks in parkinson's disease. *IEEE J Biomed Health Informl*, 19(6):1777–1793, 2015.

S. Patel, H. Park, P. Bonato, and et al. A review of wearable sensors and systems with application in rehabilitation. *J Neuroeng Rehabil*, 9(21):1–17, 2012.

A. Phinyomark, C. Limsakul, and P. Phukpattaranont. A novel feature extraction for robust emg pattern recognition. *Physiological measurement*, 1(1):71–80, 2009.

A. Phinyomark, P. Phukpattaranont, and C. Limsakul. Feature reduction and selection for emg signal classification. *Expert Systems with Applications*, 39(8):7420–7431, 2012.

R. Plamondon. A kinematic theory of rapid human movements. part i. movement representation and generation. *Biol Cybern*, 72(4):295–307, 1995.

M. Potter-Nerger, R. Wenzelburger, G. Deuschl, and et al. Impact of subthalamic stimulation and medication on proximal and distal bradykinesia in parkinson's disease. *Eur Neurol*, 62(2):114–119, 2009.

A. Prochazka, DJ. Bennett, MJ. Stephens, and et al. Measurement of rigidity in parkinson's disease. *Mov Disord*, 12(1):24–32, 1997.

AM. Qamar, Khan AR., SO. Husain, and et al. A multi-sensory gesture-based occupational therapy environment for controlling home appliances. In *Proceedings of the 5th ACM on International Conference on Multimedia Retrieval*, pages 671–674, 2015.

Lawrence R Rabiner and Bernard Gold. *Theory and application of digital signal processing*. Prentice-Hall, Inc., Englewood Cliffs, NJ, 1975.

Md Abdur Rahman and M Shamim Hossain. A gesture-based smart home-oriented health monitoring service for people with physical impairments. In *International Conference on Smart Homes and Health Telematics*, pages 464–476. Springer, 2016.

AH Rajput, B Rozdilsky, and Alex Rajput. Accuracy of clinical diagnosis in parkinsonism—a prospective study. *Can J Neurol Sci*, 18(3):275–278, 1991.

Ali H Rajput. Levodopa prolongs life expectancy and is non-toxic to substantia nigra. *Parkinsonism & Related Disorders*, 8(2):95–100, 2001.

C. Rasmussen and C. Williams. *Gaussian processes for machine learning*. The MIT Press, 2006.

Ryan Rifkin and Aldebaro Klautau. In defense of one-vs-all classification. *Journal of machine learning research*, 5(Jan):101–141, 2004.

Saara M Rissanen, Verneri Ruonala, Eero Pekkonen, Markku Kankaanpää, Olavi Airaksinen, and Pasi A Karjalainen. Signal features of surface electromyography in advanced parkinson's disease during different settings of deep brain stimulation. *Clinical Neurophysiology*, 126(12):2290–2298, 2015.

JA. Robichaud, KD. Pfann, CL. Comella, and et al. Effect of medication on emg patterns in individuals with parkinson's disease. *Mov Disord*, 17(5):950–960, 2002.

V Ruonala, E Pekkonen, S Rissanen, O Airaksinen, G Miroshnichenko, M Kankaanpää, and P Karjalainen. Dynamic tension emg to characterize the effects of dbs treatment of advanced parkinson's disease. In *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*, pages 3248–3251. IEEE, 2014.

Davud Sadihov, Bastian Migge, Roger Gassert, and Yeongmi Kim. Prototype of a vr upper-limb rehabilitation system enhanced with motion-based tactile feedback. In *World Haptics Conference (WHC), 2013*, pages 449–454. IEEE, 2013.

Sanjay Salgado, Nori Williams, Rima Kotian, and Miran Salgado. An evidence-based exercise regimen for patients with mild to moderate parkinson's disease. *Brain sciences*, 3(1):87–100, 2013.

Mithileysh Sathiyanarayanan and Sharanya Rajan. Myo armband for physiotherapy healthcare: A case study using gesture recognition application. In *Communication Systems and Networks (COMSNETS), 2016 8th International Conference on*, pages 1–6. IEEE, 2016.

Ladan Shams and Aaron R Seitz. Benefits of multisensory learning. *Trends in cognitive sciences*, 12(11):411–417, 2008.

K. Shima, T. Tsuji, E. Kan, and et al. Measurement and evaluation of finger tapping movements using magnetic sensors. In *Proceedings of the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS)*, pages 5628–5631, 2008.

K. Shima, T. Tsuji, and A. et al. Kandori. Measurement and evaluation of finger tapping movements using log-linearized gaussian mixture networks. *Sensors*, 9(3): 2187–2201, 2009.

Ho-Sun Shin, Asilbek Ganiev, and Kang-Hee Lee. Design of a virtual robotic arm based on the emg variation. *Proc. ASTL*, 2015.

Nicola Smania, Barbara Montagnana, Silvia Faccioli, Antonio Fiaschi, and Salvatore M Aglioti. Rehabilitation of somatic sensation and related deficit of motor control in patients with pure sensory stroke. *Archives of physical medicine and rehabilitation*, 84(11):1692–1702, 2003.

M. Sokolova and G. Lapalme. A systematic analysis of performance measures for classification tasks. *Information Processing and Management*, 45(4):427–437, 2009.

MW. Spong, S. Hutchinson, and M. Vidyasagar. *Robot Modeling and Control*. John Wiley and Sons, 2006.

Julien Stamatakis, Jérome Ambroise, Julien Crémers, Hoda Sharei, Valérie Delvaux, Benoit Macq, and Gaëtan Garraux. Finger tapping clinimetric score prediction in parkinson's disease using low-cost accelerometers. *Computational intelligence and neuroscience*, 2013:1, 2013.

JA Stamford, PN Schmidt, and KE Friedl. What engineering technology could do for quality of life in parkinson's disease: A review of current needs and opportunities. *J Biomed Health Inform*, 19(6):1862–1872, 2015.

Y. Su, D. Geng, CR. Allen, and et al. Three-dimensional motion system ("data-gloves"): Application for parkinson's disease and essential tremor. In *Proceedings of the IEEE International Workshop on Virtual and Intelligent Measurement Systems (VIMS)*, pages 28–33, 2001.

Y. Su, CR. Allen, D. Geng, and et al. 3-d motion system ("data-gloves"): Application for parkinson's disease. *IEEE Trans. Instrum. Meas.*, 52(3):662–674, 2003.

Nina L Suresh, Nicole S Concepcion, Janina Madoff, and WZ Rymer. Anomalous emg–force relations during low-force isometric tasks in hemiparetic stroke survivors. *Experimental brain research*, 233(1):15–25, 2015.

Edward Taub, NE Miller, TA Novack, EW Cook 3rd, WC Fleming, CS Nepomuceno, JS Connell, and JE Crago. Technique to improve chronic motor deficit after stroke. *Archives of physical medicine and rehabilitation*, 74(4):347–354, 1993.

Amanda G Thrift, Helen M Dewey, Richard AL Macdonell, John J McNeil, and Geoffrey A Donnan. Incidence of the major stroke subtypes. *Stroke*, 32(8):1732–1738, 2001.

Robert Tibshirani. Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 267–288, 1996.

Eduardo Tolosa, Gregor Wenning, and Werner Poewe. The diagnosis of parkinson's disease. *The Lancet Neurology*, 5(1):75–86, 2006.

Evanthia E Tripoliti, Alexandros T Tzallas, Markos G Tsipouras, George Rigas, Panagiota Bougia, Michael Leontiou, Spiros Konitsiotis, Maria Chondrogiorgi, Sofia Tsouli, and Dimitrios I Fotiadis. Automatic detection of freezing of gait events in patients with parkinson's disease. *Computer methods and programs in biomedicine*, 110(1):12–26, 2013.

L. Vaisman, L. Dipietro, and H. Krebs. A comparative analysis of speed profile models for wrist pointing movements. *IEEE Trans Neural Syst Rehabil Eng*, 21(5):756–766, 2013.

Miquel Vila and Serge Przedborski. Genetic clues to the pathogenesis of parkinson's disease. 2004.

Jens Volkmann. Update on surgery for parkinson's disease. *Current opinion in neurology*, 20(4):465–469, 2007.

Charles P Warlow, Jan Van Gijn, Martin S Dennis, Joanna M Wardlaw, John M Bamford, Graeme J Hankey, Peter AG Sandercock, Gabriel Rinkel, Peter Langhorne, Cathie Sudlow, et al. *Stroke: practical management*. John Wiley & Sons, 2011.

David Webster and Ozkan Celik. Experimental evaluation of microsoft kinect's accuracy and capture rate for stroke rehabilitation applications. In *Haptics Symposium (HAPTICS), 2014 IEEE*, pages 455–460. IEEE, 2014.

A. Wilson and A. Bobick. Parametric hidden markov models for gesture recognition. *IEEE transactions on pattern analysis and machine intelligence*, 21(9):884–900, 1999.

Richard D Wilson, Stephen J Page, Michael Delahanty, Jayme S Knutson, Douglas D Gunzler, Lynne R Sheffler, and John Chae. Upper-limb recovery after stroke: A randomized controlled trial comparing emg-triggered, cyclic, and sensory electrical stimulation. *Neurorehabilitation and neural repair*, 30(10):978–987, 2016.

Henry J Woodford and Christopher IM Price. Emg biofeedback for the recovery of motor function after stroke. *The Cochrane Library*, 2007.

Chenguang Yang, Sai Chang, Peidong Liang, Zhijun Li, and Chun-Yi Su. Teleoperated robot writing using emg signals. In *Information and Automation, 2015 IEEE International Conference on*, pages 2264–2269. IEEE, 2015.

M Yokoe, R Okuno, T Hamasaki, Y Kurachi, K Akazawa, and S Sakoda. Opening velocity, a novel parameter, for finger tapping test in patients with parkinson's disease. *Parkinsonism & Related Disorders*, 15(6):440–444, 2009.

Juan Manuel Ibarra Zannatha, Alejandro Justo Malo Tamayo, Ángel David Gómez Sánchez, Jorge Enrique Lavín Delgado, Luis Eduardo Rodríguez Cheu, and Wilson Alexander Sierra Arévalo. Development of a system based on 3d vision, interactive virtual environments, ergonometric signals and a humanoid for stroke rehabilitation. *Computer methods and programs in biomedicine*, 112(2):239–249, 2013.

H. Zhou and H. Hu. Human motion tracking for rehabilitation – a survey. *Biomed Signal Process Control*, 3(1):1–18, 2008.

БИОГРАФИЈА

Софија Спасојевић, мастер инжењер електротехнике, рођена је 07.09.1987. године у Шапцу, република Србија. Основну школу и гимназију завршила је у Шапцу као један од најбољих ученика. У току школовања учествовала је на такмичењима из математике.

Електротехнички факултет у Београду уписала је 2006/2007. школске године. Дипломирала је 2010. године на одсеку сигнали и системи са просечном оценом 8.91 током студија и оценом 10 на дипломском. Школске 2010/2011. године уписала је мастер студије на Електротехничком факултету у Београду. Мастер студије је завршила 2011. године са просечном оценом 10 и оценом на мастер раду 10. Школске 2011/2012. године уписала је докторске студије на Електротехничком факултету у Београду, одсек управљање системима и обрада сигнала.

У јануару 2012. године, засновала је радни однос у Институту Михајло Пупин, Центар за роботику, где је запослена и данас на позицији истраживач сарадник. У јулу 2013. године уписала је билатералне докторске студије између Електротехничког факултета у Београду и Високог Техничког Института у Лисабону.

Била је ангажована на шест истраживачких пројеката, од којих је један национални (ИИИ-44008: "Развој робота као средства за превазилажење препрека у развоју деце са поремећајима") и пет интернационалних пројеката ((1) "Creative Alliance in Robotics Research and Education Focused on Medical and Service Robotics (CARE-robotics)", Project ID: IZ74Z0_137361/1, SNSF SCOPES IP; (2) "Synthesis of Collaborative Behavior Attributes with Service Robots Based on Visually-Motor Human-Machine Interaction" (COLBAR); (3) European research and development program HORIZON 2020, Coordination support activity project "Researchers' night - FLIRT"; (4) "Advanced perception and learning for cognitive heterogeneous robots" and (5) "Building attributes of artificial emotional intelligence aimed to make robots feel and sociable as humans (Emotionally Intelligent Robots - EIrobots)", Contract no. 3.4-IP-DEU/112623).

Области њеног научног истраживања обухватају обраду сигнала, машинско учење, анализу података и компјутерску визију. Објавила је укупно осамнаест научних радова, од којих два рада у међународним часописима, пет поглавља у књигама издавача Шпрингер, пет радова који су презентовани на интернационалним конференцијама и шест радова на домаћим конференцијама.

Изјава о ауторству

Име и презиме аутора Софија Спасојевић

Број индекса 5014/2011

Изјављујем

да је докторска дисертација под насловом

Квантитативна анализа покрета у рехабилитацији неуролошких поремећаја коришћењем визуелних и носивих сензора

- резултат сопственог истраживачког рада;
- да дисертација у целини ни у деловима није била предложена за стицање друге дипломе према студијским програмима других високошколских установа (билатерални докторски програм са Универзитетом у Лисабону);
- да су резултати коректно наведени и
- да нисам кршио/ла ауторска права и користио/ла интелектуалну својину других лица.

Потпис аутора

У Београду, 26.10.2017.

Софија Спасојевић

Изјава о истоветности штампане и електронске верзије докторског рада

Име и презиме аутора Софија Спасојевић

Број индекса 5014/2011

Студијски програм Управљање системима и обрада сигнала

Наслов рада Квантитативна анализа покрета у рехабилитацији неуролошких поремећаја коришћењем визуелних и носивих сензора

Ментор проф. др Жељко Ђуровић и проф. др José Santos-Victor

Изјављујем да је штампана верзија мог докторског рада истоветна електронској верзији коју сам предао/ла ради похрањена у **Дигиталном репозиторијуму Универзитета у Београду.**

Дозвољавам да се објаве моји лични подаци везани за добијање академског назива доктора наука, као што су име и презиме, година и место рођења и датум одбране рада.

Ови лични подаци могу се објавити на мрежним страницама дигиталне библиотеке, у електронском каталогу и у публикацијама Универзитета у Београду.

Потпис аутора

У Београду, 26.10.2017.

Софија Спасојевић

Изјава о коришћењу

Овлашћујем Универзитетску библиотеку „Светозар Марковић" да у Дигитални репозиторијум Универзитета у Београду унесе моју докторску дисертацију под насловом:

Квантитативна анализа покрета у рехабилитацији неуролошких поремећаја коришћењем визуелних и носивих сензора

која је моје ауторско дело.

Дисертацију са свим прилозима предао/ла сам у електронском формату погодном за трајно архивирање.

Моју докторску дисертацију похрањену у Дигиталном репозиторијуму Универзитета у Београду и доступну у отвореном приступу могу да користе сви који поштују одредбе садржане у одабраном типу лиценце Креативне заједнице (Creative Commons) за коју сам се одлучио/ла.

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(Молимо да заокружите само једну од шест понуђених лиценци.
Кратак опис лиценци је саставни део ове изјаве).

Потпис аутора

У Београду, 26.10.2017.

Ристија Ристојевић