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SPORTS PERFORMANCE MEASUREMENT USING KINEMATIC SENSORS

Doctoral Dissertation

Belgrade, 2022

UNIVERZITET U BEOGRADU
FAKULTET SPORTA I FIZIČKOG VASPITANJA

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MERENJE PERFORMANSI U SPORTU PRIMENOM KINEMATIČKIH SENZORA

doktorska disertacija

Beograd, 2022

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Acknowledgments

This dissertation has been done as a part of the project "Effects of the Applied Physical Activity on Locomotor, Metabolic, Psychosocial and Educational Status of the Population of the Republic of Serbia", number III47015, funded by the Ministry of Education, Science and Technological Development of the Republic of Serbia-Scientific Projects 2011–2019 Cycle.

This dissertation has been done as a part of the Slovenian Research Agency research program ICT4QoL-Information and Communications Technologies for Quality of Life (research core funding no. P2-0246).

This dissertation has been done as a part of the bilateral project between Slovenia and Serbia titled "Sensor technologies as support systems for the detection and selection of talents in sport and monitoring the performance of athletes" (research core funding no. BI-RS/20-21-023).

This dissertation has been done as a part of the Erasmus+ International Credit Mobility between the University of Belgrade, Faculty of Sport and Physical Education, and the University of Ljubljana, Faculty of Electrical Engineering in the period 23.09.2019. - 20.02.2020.

Material presented in this dissertation is based on the results that were published in international scientific journals with WoS IF of 1.781 to 3.576:

1. **Marković, S.**, Dopsaj, M., Tomažič, S., & Umek, A. (2020). Potential of IMU-Based Systems in Measuring Single Rapid Movement Variables in Females with Different Training Backgrounds and Specialization. *Applied Bionics and Biomechanics*, 2020, Article ID 7919514. https://doi.org/10.1155/2020/7919514, M23, WoS IF=1.781

2. **Marković, S.**, Dopsaj, M., Umek, A., Prebeg, G., & Kos, A. (2020). The Relationship of Pistol Movement Measured by a Kinematic Sensor, Shooting Performance and Handgrip Strength. *International Journal of Performance Analysis in Sport*, 20(6). https://doi.org/10.1080/24748668.2020.1833624, M23, WoS IF=1.950

3. **Marković, S.**, Kos, A., Vuković, V., Dopsaj, M., Koropanovski, N., & Umek, A. (2021). Use of IMU in Differential Analysis of the Reverse Punch Temporal Structure in Relation to the Achieved Maximal Hand Velocity. *Sensors*, 21(12), 4148. https://doi.org/10.3390/s21124148, M21, WoS IF=3.576

4. **Marković, S.**, Dopsaj, M., Tomažič, S., Kos, A., Nedeljković, A., & Umek, A. (2021). Can IMU Provide an Accurate Vertical Jump Height Estimate? *Applied Sciences (Basel)*, 11(24). https://doi.org/10.3390/app112412025, M22, WoS IF=2.679

All studies have been conducted in accordance with the postulates of the Declaration of Helsinki and were approved by the Ethics Committee of the University of Belgrade Faculty of Sport and Physical Education (02 No. 484-2).

Dedication

I would like to thank Dr. Anton Umek and Dr. Anton Kos.

I would like to thank Dr. Milivoj Dopsaj.

I would like to thank my family.

Sports Performance Measurement Using Kinematic Sensors

Resume

The main aim of this work was to determine the potential of kinematic sensors regarding estimation of bio-motor abilities and measurement of movement kinematics in precision, rapid movement, and complex tasks. This was achieved in four separate studies that addressed the topics of rapid hand movements, precision pistol shooting, karate reverse punch, and vertical jump. The main motivation of this work is to provide in-field support for periodic measurements in training. The findings of the first study presented in this work have shown that kinematic sensors are applicable for the measurement of human movement kinematics in non-specific rapid movement tasks. In addition, the temporal variables of movement have been shown to have the highest discriminative potential in relation to the assessment, monitoring, and selection of athletes in this regard. The findings of the second study presented in this work support the applicability of kinematic sensors to measure precision tasks, more precisely, precision shooting tasks. The results indicate high practical importance of the rotational component of weapon movement on shooting performance, which gets more pronounced with shooting distance. In addition, the last part of the shooting task, which corresponds to the trigger pull phase has been identified as most important, which further supports the applicability of kinematic sensors in this context. The findings of the third study presented in this work have shown that multiple synchronized kinematic sensors can be successfully used for tracking movement synchronization in sequential rapid movement task, more precisely the karate reverse punch. The results confirm a different temporal pattern in high-velocity strikes. However, proximal-to-distal sequencing is also a characteristic of throwing movements. Thus, the findings are applicable in this context. The fourth study presented in this work has shown that a kinematic sensor provides valid and reliable results regarding vertical jump height estimate when compared to a force plate. This implies that kinematic sensors can be used for in-field vertical jump height assessments, i.e. testing athletes' bio-motor abilities.

Overall, this work has pointed out the applicability of kinematic sensors in the measurement of movement kinematics in different sports tasks, which adds to the existing body of knowledge in this area. In addition, this work has shown that a conceptual simplification of the task and appropriate signal and/or parameter analysis can provide excellent results in augmenting the amount of available feedback information that can be used for improvements in training.

Keywords: kinematic sensors, IMU, vertical jump, jump height, CMJ, SQJ, pistol shooting, precision, accuracy, karate, reverse punch, punch velocity, rapid hand movement, group discrimination, performance

Scientific field: Physical Education and Sport
Scientific subfield: Science of Physical Education, Sports, and Recreation
UDC number: 796.012.1(043.3)

Merenje Performansi U Sportu Primenom Kinematičkih Senzora

Rezime

Glavni cilj ovog rada je da se utvrdi potencijal kinemtičkih senzora u odnosu na procenu bio-motoričkih sposobnosti i merenje kinematike kretanja u preciznim, brzim pokretima i kompleksnim motoričkim zadacima. Ovo je postignuto u četiri odvojene studije koje su se bavile brzim pokretima ruke, preciznim gađanjem iz pištolja, gzaku zuki karate udarcem i vertikalnim skokom. Glavna motivacija za ovaj rad je da se stvori mogućnost za periodično merenje u treningu. Rezultati prve studije u ovom radu su pokazali da su kinematički senzori primenljivi za potrebe merenja kinematike ljudskog kretanja u nespecifičnim brzim pokretima. Takođe, pokazano je da vremenske varijable kretanja imaju najveći diskriminativni potencijal u odnosu na procenu, praćenje i selekciju sportista u ovom pogledu. Rezultati druge prikazane studije podržavaju primenljivost kinematičkih senzora za merenje preciznih kretnih zadataka, odnosno preciznih zadataka u streljaštvu. Rezultati ukazuju na visoku praktičnu značajnost rotacione komponente kretanja oružja na rezultat, što postaje izraženije sa distancom. Takođe, poslednji deo hica, koji odgovara fazi povlačenja okidača je identifikovan kao najvažniji, što dodatno podržava primenljivost kinematičkih senzora u ovom kontekstu. Rezultati treće prikazane studije su pokazali da više sinhronizovanih kinemetičkih senzora može biti uspešno korišćeno za praćenje sinhronizacije sekvencijalnih brzih pokreta, preciznije gyaku zuki karate udarcu. Rezultati potvrđuju različitu vremensku strukturu kod udaraca velike brzine. Ipak, proksimalno-distalno slaganje kretanja je karakteristično i za pokrete bacanja. Posledično, ovi nalazi se mogu primeniti i u ovom kontekstu. Četvrta prikazana studija je pokazala da kinematički senzori daju validne i ponovljive rezultate u odnosu na procenu visine vertikalnog skoka, poređeno sa platformom sile. Ovo ukazuje da se kinemetički senozori mogu koristiti za terensku procenu visine vertikalnog skoka, odnosno testiranje statusa bio-motoričkih sposobnosti.

Sumarno, ovaj rad je pokazao primenljivost kinematičkih senzora u merenju kinematike kretanja u različitim sportskim zadacima, što nadgrađuje postojeći fundus znanja u ovoj oblasti. Dodatno, ovaj rad je pokazao da konceptualno pojednostavljenje problemskog zadatka i adekvatna analiza signala i/ili parametara može dati odlične rezultate u smislu povećanja količine dostupnih povratnih informacija koje se mogu koristiti za unapređenje treninga.

Ključne reči: kinematički senzori, IMU, vertikalni skok, visina skoka, CMJ, SQJ, gađanje iz pištolja, preciznost, tačnost, karate, gyaku zuki, brzina udarca, brzi pokreti ruke, kategorizacija grupa, performasa

Naučna oblast: Fizičko vaspitanje i sport
Uža naučna oblast: Nauke fizičkog vaspitanja, sporta i rekreacije
UDK broj: 796.012.1(043.3)

Contents

1. Introduction

The increasingly fast development of sports science is accompanied by an integrative, multi-structured approach to information gathering using a variety of equipment in in-field and laboratory testing conditions. Relevant information regarding the achieved level of physical preparedness of the athletes during different phases of long-term preparation is acquired using multiple measurement methods and technologies. The obtained results can serve as a basis for the purposes of assessment, as well as to calculate the potential of physical abilities and the efficiency of the athletes' performance. Overall, the system of sport is very diversified and complex in terms of movement types and characteristics.

The measurement of performance is an integral part of sports training, competition, and rehabilitation. In short, it is a core element of the management of training that enables deterministic manipulation of the three aforementioned processes. In any and all cases sports performance measurement is done for a specific purpose. This specific purpose is the quantification of state, or the change of state, of the skills and bio-motor abilities that are found to be relevant for each specific sport. This numerical representation of the selected skill/ability is used for unbiased evaluation and decision making, ultimately leading to performance improvements.

One of the ways to quantify human movement kinematics is the application of miniature kinematic sensors. Kinematic sensors, namely accelerometer and gyroscope measure physical quantities of acceleration and angular rotation. Mathematical processing of the acquired sensor signals provides additional derived quantities for a more complete analysis. Kinematic sensors are used as a basis for different systems of various complexity which are used to provide data on kinematic characteristics of aggregated, segmental or full-body movements. Modern kinematic sensors have several significant pros, some of which are small size and weight, portability, and low price. However, the primary reason for movement quantification using kinematic sensors lies in the fact that the results can augment the amount of information available to the athletes and coaches.

This work addresses the application of kinematic sensors as a tool for the measurement and evaluation of sports performance in structurally different tasks. These are hand tapping, precision pistol shooting, karate reverse punch, and vertical jump. The main motivation of this work is to provide in-field support for periodic measurements in training. The selected individual tasks actually represent examples of a rapid movement task, precision task, complex movement task, and a test of physical, i.e. bio-motor ability, respectively. Since these tasks are highly unrelated to each other, they are addressed in separate studies presented in this work.

The first of the presented studies addresses the problem of selection and categorization of athletes based on the kinematic data acquired in a non-specific rapid movement task. The second study addresses the relation of weapon movement kinematics and shooting performance in live-fire precision pistol shooting. The third study is aimed to provide implicit information on the movement synchronization in a karate reverse punch based on its temporal structure. The fourth study addresses the in-field measurement of vertical jump height.

2. Theoretical basis

This section is divided into two parts. The first addresses the relevant concepts of the theory and technology of sports training. These individual concepts are interconnected to form a theoretical basis of this work regarding the general purpose of the application of kinematic sensors in sports training. The second subsection addresses the concepts of design, function, and implementation of kinematic sensors as a tool for kinematic analysis of human movements. Although the two sections are separate, their combined content forms an overall context which served as a basis for this work.

2.1. Management of training

The overall physiological homeostasis can be defined as the natural state of internal equilibrium between the interdependent elements of the human organism (Martini et al., 2018). At any given point in time, the human body is trying to reach or retain this state. The disturbance of homeostasis triggers arguably the most important mechanism in all biological systems, adaptation. In a broad sense, adaptation is the process of change resulting in an adjustment of the organism (Zatsiorsky & Kraemer, 2006) to suit the altered conditions. The core of the adaptation process is related to the notion of stress, i.e. physiological or physical stimulus that elicits a specific response of an organism to adapt. The ability of an individual to adapt in a response to a particular type of stress is not fixed and can be enhanced by prolonged exposure to that stress (Raff et al., 2014). However, the induced adaptive changes are generally reversible.

In general, physical training is just a form of stress that induces necessary adaptations in accordance with the imposed specific demands of the task (L. E. Brown, 2007) in order to provide better preconditions for competitive performance. On the other hand, competition is also a form of stress. Thus, it can be argued that athletes need to adapt to the combined effects of the two (Koprivica, 2013). A three-phase process depicts the reaction of the body to the imposed stressful demands. The initial response includes a temporary reduction in performance. If certain conditions are met this can be followed by a specific adaptation which can, again depending on the conditions, be followed by recovery or exhaustion. The former can facilitate further adaptation, while the latter can lead to performance reduction, over-training, and injury (L. E. Brown, 2007). The main consequence of this progression, also known as the general adaptation syndrome, is the need for systematic manipulation of the components of training load in order to produce specific adaptive effects (Milišić, 2003).

The specific adaptive effects of training are roughly divided into acute, delayed, and cumulative (Koprivica, 2013). Systematic manipulation of these effects provides a link that lies in the foundation of the periodization of the training process. Periodization of sports training involves two basic concepts: periodization of the annual training plan and periodization of bio-motor abilities (Bompa & Buzzichelli, 2015). The main goal is to optimize the relationship between the training load and heterochronous processes of recovery and adaptation in order to enable progressive bio-motor development and timely peak performance. Essentially, periodization represents the long-term management of the interrelated components of the training process by decomposition of sports training (Koprivica, 2013) into logical parts. This is fundamental to the system of preparation of the athletes as it enables optimal development of bio-motor abilities and improvement of sport-specific skills (Milišić, 2003), all aimed toward successful performance on main competitive events. Both development of bio-motor abilities and skill acquisition and improvement represents a process of adaptation to the introduced sport-specific demands. However, the transitory character of the individual phases of this process imposes the need for quantification of the state and changes of the fore-mentioned abilities and skills.

Quantification is generally fundamental to the scientific method. It is the expression of an event in numeric terms done by the application of a test or instrument (Morrow et al., 2005). As the management of the training process represents a deterministic system, the future training focus is based on accurate insight into athletes' current status (McMahon et al., 2017) in regard to both specific skills and bio-motor abilities. In this sense, measurement provides the necessary data in relation to the state, or the change of state, of physiological and biomechanical parameters of the human movement (Dopsaj, 2015). However, only when the data is interpreted within a context it becomes a useful piece of information. And information is critical to any decision-making process, including the management of sports training. On the other hand, not only that the acquired information is relevant to the long-term management of training, but can be used to modify the content of individual training sessions if provided to the coaches and athletes in a form of augmented feedback (Kos & Umek, 2018a).

Augmented feedback is an enhancement to the capabilities of the human senses. It is the presentation of additional information, which can ultimately lead to accelerated motor learning and better training progression. Augmented feedback can be concurrent or terminal (Kos & Umek, 2018a) in relation to the time of presentation, and physiological or biomechanical (Giggins et al., 2013) in relation to the origin of the acquired parameters. Preferably, augmented feedback should not cause additional cognitive load (Stojmenova et al., 2018) and should be delivered via a less employed sensory channel. Due to the fact that decomposition of the periodization ultimately leads to the microstructure of training and its fundamental unit - an individual training session (Koprivica, 2013), augmented feedback is a vital part of the process of management of sports training. In a deterministic system of management of sports training, augmented feedback enables more precise manipulation of the components of training load. This is in order to compensate for the (un)expected effects of periodic fluctuations in the state of the athletes' physiological capacities and bio-motor abilities (Koprivica, 2013; Stefanović & Jakovljević, 2004), as well as to enable fine-tuning of the training structure to better reflect, or rather preserve, the long-term goal of a larger structural unit.

The management of training represents an integrated system that heavily relies on relevant and timely information in order to be successful. It is composed of several components, namely laboratory testing, monitoring of training effects, and performance analysis (Milišić, 2003). While laboratory testing leverages the equipment to provide an in-depth view into specific skills and bio-motor abilities, monitoring of the training effects includes the application of in-field tests (Dopsaj, 2015) to provide information on the progression of the ones that are the most relevant. Equipment for in-field use tends to be less expensive, less bulky, and easier to operate. However, it is usually less accurate and is thus validated against reference laboratory equipment. Periodic and permanent monitoring of the development of the athletes is enabled by application of laboratory and in-field testing, respectively.

Learned movements are often termed skills. Sport-specific skills are no exception, but rather an example. They are not inherited, and experience of long periods of practice is a prerequisite for mastering them (Schmidt et al., 2018). On the other hand, bio-motor abilities are just conditional motor capacities or general physical qualities that affect performance (Bompa & Buzzichelli, 2015). Let's settle for these being strength, power, speed, flexibility, endurance, and coordination (Kukolj, 2006). But what essentially these skills and abilities are? In a nutshell, just adaptations of multiple physiological systems. However, they are aggregated and manifested jointly as movement is a mechanical outcome of skeletal muscle contraction (Oatis, 2016). And that mechanical outcome is quantifiable.

Mechanics is the field of science concerned with the study of the motion of objects while biomechanics extends the principles to biological systems (Blazevich, 2007). Rigid-body mechanics is the emphasis of biomechanics as it is applicable to describe the gross movements of humans and implements (P. M. McGinnis, 2013). A subdivision of mechanics is kinematics. It is concerned with the description of motion in terms of position, velocity, orientation, angular velocity, etc. without consideration of the involved forces (Jarić, 1997; P. M. McGinnis, 2013). The kinematic characteristics of human motion can be divided into spatial, temporal, and spatiotemporal (Ilić et al., 2009). Kinematic variables of human motion are measured as a part of quantitative biomechanical analysis, using systems of various complexity including single or multiple kinematic sensors as well as full motion capture (MoCap) systems (P. M. McGinnis, 2013).

To summarize, in order to achieve the best results athletes need to develop their skills and bio-motor abilities to the highest possible extent. This is done through the process of adaptation triggered by repeated exposure to physiological and physical stress caused by systematic manipulation of the components of the training load. Periodization is used to fully utilize the summation of the different training effects in order to stimulate the desired adaptations. It forms the basis for the long-term management of training which heavily relies on relevant and timely information provided by periodic and permanent monitoring of training and performance. The quantification of skills and abilities of interest is done using laboratory testing, monitoring of training effects, and performance analysis. On the other hand, short-term management of training benefits from augmented feedback. In both cases, an insight into the kinematic characteristics of human motion can be achieved by means of quantitative biomechanical analysis using different applicable equipment such as kinematic sensors.

2.2. Kinematic sensors

Motion capture systems (MoCap) are used in order to capture and track human movement (P. M. McGinnis, 2013). The techniques that are used can be classified as either marker-based or marker-free capture (Bregler, 2007) while the applied systems can be optical, non-optical, and marker-less (Pueo & Jimenez-Olmedo, 2017) The category of non-optical systems includes miniature kinematic sensors which are often integrated into wearable sensor devices or smart equipment. These are used for the measurement of static and dynamic states of the athlete's body (Taborri et al., 2020). In relation to the dynamics, they provide acceleration and angular velocity as well as other quantities that can be derived mathematically. Depending on the deployed configuration, multiple sensors can be integrated into a full-body motion tracking system (such as Xsens), while in certain conditions fewer sensors can be used for tracking aggregated movement.

The term MicroElectroMechanical Systems (MEMS) relates to the integrated microsystems combining electrical and mechanical components developed by the application of Integrated Circuit (IC) compatible batch-processing techniques. These systems range in size from micrometers to millimeters (Mishra et al., 2019). In relation to the core area of application, inertial sensors are a subdivision of MEMS (Maluf, 2004; Mishra et al., 2019) This technological advance allows measurement capability without limited space constraints and other constraints inherent to the optical motion capture systems. The two common types of inertial MEMS are accelerometers and gyroscopes that measure acceleration and angular rotation, respectively. They are often combined into a single kinematic sensor device. A possible addition to the pair is a magnetometer that measures the magnetic field. Additional quantities, such as velocity, position, and jerk as well as their rotational counterparts can be mathematically derived from the acquired signals. In addition, when provided with an appropriate sensor fusion algorithm, the combination of the three aforementioned sensors allows for the calculation of the absolute sensor orientation and relative position. The functioning principle of inertial sensors is based on Newton's second law which states that the net force acting on a body is equal to the product of the body's mass and its acceleration (Halliday et al., 2013).

A 3D accelerometer contains a triad of integrated perpendicular accelerometers. Each accelerometer has a movable proof mass connected to a fixed frame via spring structures (Figure 2.1). This enables full quantification of the movement in relation to the Cartesian coordinate frame with the origin in the center of the accelerometer triad and axes aligned to the casing. This frame is used to resolve all inertial measurements (Silva, 2014). It is essential to notice that the accelerometer in fact measures force as it basically captures the changes in linear acceleration along an axis through a force-detection mechanism. An external force produces a proportional displacement of the proof mass from its position at rest relative to the fixed sensor frame. Sensor proof mass displacement is converted into an electrical signal by capacitive mechanisms (Maluf, 2004) as illustrated in Figure 2.1. As accelerometers are gravity sensitive the orientation affects the output value which represents the vector sum of gravity and movement acceleration.

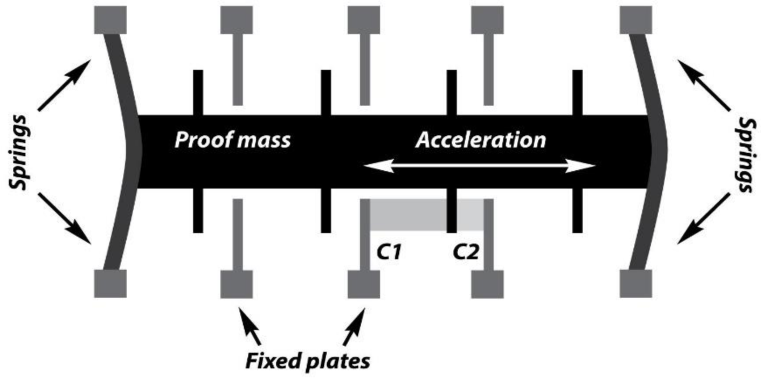

Figure 2.1: Uniaxial accelerometer working principle; The reactive proof mass is suspended by the springs; The displacement of the proof mass is detected by the capacitance change on the fixed plates;

MEMS gyroscopes are motion sensors that detect and measure the angular motion of an object in three dimensions. More precisely, they measure the angular velocity of an object around a particular axis (Passaro et al., 2017; Silva, 2014). The working principle is similar to the accelerometer in the sense that the angular velocity is measured through a force-detection mechanism. However, gyroscopes measure the apparent deflecting force of rotation, i.e. the Coriolis force (Menzel, 1960). In order to induce the Coriolis effect the sensor mass is kept in a continuously oscillating movement while the pairing of proof masses into a tuning fork makes the system insensitive to linear acceleration. An angular rate produces a proportional displacement of the proof mass from its position at rest relative to the fixed sensor frame. This displacement is also converted into an electrical signal by capacitive mechanisms (Maluf, 2004).

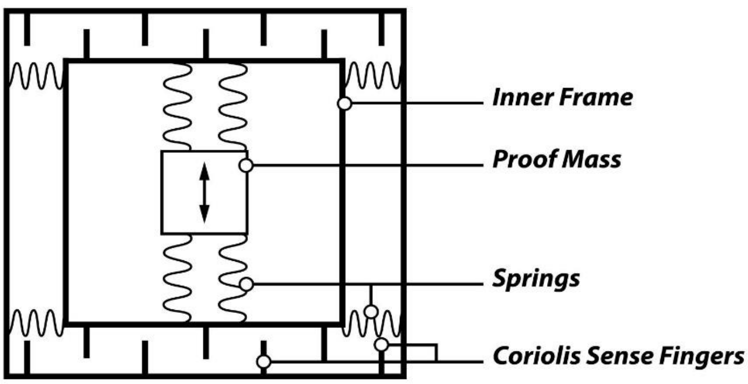

Figure 2.2: Gyroscope working principle; The outer fixed frame suspends the inner frame containing the oscillating proof mass; The displacement of the proof mass caused by the Coriolis effect is detected by the capacitance change on the fixed plates;

As aforementioned the physical quantities measured by an accelerometer and a gyroscope are acceleration and angular velocity, respectively. Table 2.1 provides an overview of additional relevant physical quantities that can be mathematically derived from the two sensors (Halliday et al., 2013). Here it is important to notice that the known relationship between the measures provides additional information related to the movement analysis as well as to the inherent constraints of the system.

Regarding the former, stationary, turning, and inflection points in a time series of the acquired signal implicitly provide the location of their mathematically derived counterparts (Bartlett, 2007). This serves as an extension to the temporal analysis. On the other hand, the process of integration introduces inflation of sensor bias error proportional to t raised to the power of the number of integrations.

Table 2.1: Mathematical relationship between the measured and derived quantities

Displacement	Velocity	**Acceleration**	Jerk
$d(t) = \int(\int a(t)dt)dt$	$v(t) = \int a(t)dt$	$\boldsymbol{a(t)}$	$j(t) = da/dt$
Angular displacement	**Angular velocity**	Angular acceleration	Angular jerk
$\theta(t) = \int \omega(t)dt$	$\boldsymbol{\omega(t)}$	$a(t) = d\omega/dt$	$\zeta(t) = d^2\omega/dt^2$

The factors that induce sensor error are misalignment, scale factor, non-linearity, noise, and bias (Naranjo, 2008). Those of particular interest are bias and noise. Bias is the average sensor output at zero sensor input (Kos et al., 2016a) while the noise is a random time-varying signal (Chen, 2004) causing undesired perturbations in the sensor output. Bias can be further split into initial bias and drift, which represent the static measurement offset and a random part that varies. However, initial bias and temperature drift are deterministic in nature and thus can be determined and compensated for by calibration (Naranjo, 2008). Noise is generally uncorrelated with the sensor input (Naranjo, 2008, 2008). Thus, the effect of noise on the sensor output cannot be negated over a number of sensor samples. However, its effect on bias estimates can be reduced for short time intervals by averaging over a large number of measured signal samples (Stančin & Tomažič, 2014). In a nutshell, calibration is the process of comparing instrument output with a known reference value and modifying it to agree with the reference over a range of output values (Syed et al., 2007). Bias is the most important factor that introduces an error to the measurement results. Thus, the bias should be compensated for by regular calibration of the sensor. This is performed in a standstill position for both the gyroscope and accelerometer. However, as gravitational acceleration acts on the sensor, the proper bias compensation is dependent on the proper alignment of one of the accelerometer axes with the gravity acceleration vector.

The orientation is basically the measure of rotation of an object relative to a known reference frame. Kinematic sensor device orientation can be calculated using the gyroscope alone with rotation being specified by Euler angles, direction cosine matrix, or quaternions (Stančin & Tomažič, 2014; Syed et al., 2007). In all cases, orientation is calculated in relation to the known initial reference value. The fusion of accelerometer and magnetometer data also provides a coordinate frame that can serve for orientation calculation in a standstill position. The orientation is calculated based on the changes in the measured magnetic field and acceleration. However, the fusion of the results obtained from an accelerometer, magnetometer, and gyroscope provides absolute orientation while the system is in the state of motion. Sensor fusion algorithms are used to combine different types of filters in order to reduce the influence of errors introduced by particular sensors due to their individual limitations. This is used to provide a more accurate result (Naranjo, 2008; Zhao, 2018).

To summarize, technological advancement has allowed for the development of MEMS that combine electrical and mechanical components on a micro-scale. MEMS accelerometer and gyroscope are kinematic sensors used to quantify acceleration and angular velocity, respectively. These two sensors are often combined into a kinematic sensor device, with the possible addition of a magnetometer. In order to provide a more accurate measurement result, all sensors have to be calibrated. Mathematical processing of the acquired sensor signals provides additional derived quantities among which the ones most frequently used are orientation and velocity. However, this process introduces an increment of sensor error to the results, which represents a constraint that cannot be completely negated. More accurate measurement results are obtained by combining and filtering the signals acquired from different sensors or multiple sensor devices. Regarding the application in the area of sport kinematic-sensor-based systems are employed for quantification of the kinematics of human movement. The complexity of the applied system configuration varies.

3. Previous research

This section is divided into two parts. The first addresses some of the more interesting studies of the large available body of literature regarding the application of kinematic sensors in different sports tasks. The second part concerns the previous studies that had a significant effect on the conceptualization of the individual studies presented in the later sections of this work.

3.1. A general overview

The diversity of applications based on kinematic sensor devices used in sport-specific situations covers a wide variety of different sports and sport-specific tasks. As the number of possible applications is quite large, the provided overview covers some of the main applications areas of kinematic sensors in sports. These are:

- Walking tasks
- Sports involving an implement
- Precision tasks
- Rapid movements
- Measurement of athletes' bio-motor abilities
- Water sports

Kinematic sensors are widely implemented in the area concerning walking, and by extension running tasks. A study Flores-Morales et al. (2016) used six kinematic sensors devices attached to the lower extremities of subjects and analyzed the acquired data in order to create and analyze dynamic simulations of movement. Scalera et al. (2017) used the autocorrelation function in order to assess the regularity of cyclic human movements. Derungs et al. (2018) applied regression methods on the data acquired from 14 kinematic sensors for the estimation of acquired skills and detection of potential coordination mistakes in Nordic walking. Shiang et al. (2016) employed inertial sensors to determine the foot strike pattern and stride length for three different running speeds while Zrenner et al. (2018) compared different methodological approaches to the calculation of running speed and stride length. A study by Muniz-Pardos et al. (2018) used kinematic sensors placed on the foot in order to evaluate the running economy and foot mechanics in elite runners. Gurchiek et al. (2019) assessed sprint by application of machine learning using data acquired from an accelerometer placed on the waist. A study by Mertens et al. (2018) used GPS and kinematic sensor fusion for sprint diagnostics. Jang et al. (2018) used an XSens motion capture system with 17 body-wired inertial motion trackers to record the kinematic data of a cross-country skier. They used deep learning techniques to classify the classical and skating style cross-country techniques with the accuracy of 87.2% and 95.1% for the flat and natural course. Yu et al. (2016) used 16 kinematic sensors to determine the best location of the sensor for performance analysis of alpine skiers. The results indicate that a kinematic sensor located on the pelvis accurately reflects the total body center of mass position.

Another area common to the application of kinematic sensors in the context of measurement of sports performance includes the sports involving an implement. In this context, a work by Y. Wang, Chen, et al. (2018) aimed to differentiate badminton players of different competitive levels based on their strike performance. They applied machine learning methods to data acquired from a wrist-worn kinematic sensor device. Lim et al. (2018) used deep learning methods on data acquired from three kinematic sensors attached to the elbow, hand, and wrist of table tennis players in order to provide relevant feedback. Yang et al. (2017) performed an evaluation of tennis serves through the support vector machine method based on the data acquired from two kinematic sensors placed on the knee and wrist of the athlete. Similarly, Ahmadi et al. (2009) combined methodological approaches in order to provide strike detection and classification of the tennis serve based on the data from three gyroscope sensors placed on the athletes' chest, upper arm, and hand. The resulting accuracy of detection and classification of the three most common tennis strokes (forehand, backhand, and serve) was >98%. A similar sensor setup was used by Ghasemzadeh & Jafari (2010) for the assessment of movement coordination in the baseball swing.

A recent area of application of kinematic sensors in the system of sport involves the execution of precision tasks, such as firearm or bow shooting. Papers by Kos, Dopsaj, et al. (2019) and Kos, Umek, et al. (2019) have shown that a single kinematic sensor device can be used for tracking the relevant movement of the handgun in precision shooting situations while a paper by Dopsaj, Marković, et al. (2019) provided mathematical models of accuracy and precision for pistol shooting on different distances using the same sensor setup. R. S. McGinnis et al. (2014) have shown that a pair of kinematic sensors can be used for tracking torso pitch angles and rifle elevation and azimuth angles during rifle aiming. Ogasawara et al. (2021) used a bow-mounted accelerometer for shooting detection in archery and a decision tree method for predicting scores from the postural tremors that occur during aiming.

Rapid movement tasks are opposite to the precision tasks as defined by the speed-accuracy trade-off. Despite the different time and intensity constraints, kinematic sensors are commonly used in this area. Lapinski et al. (2019) used a system of kinematic sensors placed on the waist, chest, arm, wrist, and hand and a combination of multi-range accelerometers and gyroscopes in order to fully capture high and low dynamic components of the movement in overhead pitching. Y. Wang, Zhao, et al. (2018) reported high classification accuracy (94%) of volleyball spike skill level based on data acquired from a kinematic sensor device placed on the athletes' wrist. The same placement of the sensor was used by Ma et al. (2018) for the classification of nine different basketball movements using support vector machine classification. Shankar et al. (2018) used one kinematic sensor attached to the wrist of the athlete in order to acquire basketball player free throw shooting data and estimate performance.

Assessment of the state, or the change of state, of the athletes' bio-motor abilities is a task common to virtually all sports. In this area, for example, Abbott et al. (2020) validated kinematic sensor devices for the measurement of barbell kinematics in back squat through different loading conditions. The results indicate the good agreement with MoCap only for loads under 60% 1RM. A study by Perez-Castilla et al. (2019) validated different systems for the assessment of movement velocity in bench press on a Smith machine. The two commercially available kinematic-sensor-based systems provided the worst results. Picerno et al. (2011) used a kinematic sensor device positioned on the back of the participant in order to determine the vertical jump height. Conversely, a study by

Jaitner et al. (2015) effectively used only accelerometer data from a sensor placed on the ankle to provide accurate jump detection and height estimation.

Due to the different movement environment, water sports require a specific research approach and impose some constraints in relation to the build of the employed systems as well as communication of the results to the end-user. However, kinematic sensor devices have been used to a considerable extent in this area as shown. A study by Z. Wang et al. (2019) employed a 9 DOF kinematic sensor device to capture the posture of the human lumbar spine in swimming. This was achieved using an orientation estimation algorithm and a human biomechanical model. Kos & Umek (2018b) used a single kinematic sensor device attached to the lower back of the athlete in order to capture the most relevant swimming parameters for all four disciplines. Both studies employed offline data recording while swimming. Lecoutere & Puers (2016) used kinematic sensors in order to track elite swimmers in real-time. They used a gyroscope and accelerometer signal to calculate the most important swimming parameters and send them to the PC when the swimmer's head is out of the water.

The diversity of application of kinematic-sensor-based devices used in sport-specific situations confirms the fact that they are quite a versatile tool that can be used to tackle a wide variety of problems and situations. In addition, the extraction of kinematic parameters or other relevant results can be performed using a number of analysis techniques as appropriate in relation to the task which further broadens their applicability.

3.2. Related studies

This work focused on the application of kinematic sensors for the measurement and evaluation of sports performance in four specific tasks: hand tapping, precision pistol shooting, karate reverse punch, and vertical jump. The conceptualization of the respective parts of the work was highly influenced by several studies that are presented in the following paragraphs.

A recent paper by Umek & Kos (2021) validated a custom-built kinematic sensor device in relation to the measurement of rapid hand movement. Apart from the time elapsed for task completion, they compared the main characteristics of hand displacement, velocity, and acceleration acquired from both kinematic sensor devices and a Qualisys motion optical motion capture system on a hand tapping test. The study has determined that measurement error in relation to the hand velocity and position is in the range of 5-10% when comparing the results from the kinematic sensor device with the results from the reference system. The determined results indicate that the presented system is applicable in relation to the measurement of the rapid hand movement parameters in heterogeneous groups. The aforementioned served as a basis for conceptualization of the work regarding rapid hand movement which resulted in Study #1.

Research conducted by Pellegrini et al. (2004) related the tremor output of a goal-directed postural pointing task to the outcome change reflected on the target. The tremor was quantified using the displacement of the reflective markers on the hand segment while a laser emission trace quantified the outcome on the target. This study established the feasibility of such an approach for tremor analysis and significant tremor amplitude in lateral and vertical directions which was more pronounced for markers that were placed at a distal position, i.e. toward the endpoint of the kinetic chain. The subsequent analyses identified a low-frequency oscillation of 1.5 Hz as dominant in the displacement of the target track. An additional 5–7 Hz high-frequency component was found. These two were significantly linked to hand oscillation. The paper provided a linear regression analysis for different markers vs. target track which indicates the increase of tremor towards the kinetic chain endpoint as confirmed by the statistically significant results for the hand segment. The presented results indicate that hand displacement is reflected on the target in a 2:1 ratio on the target distance of 4m. The aforementioned served as a basis for conceptualization of the work regarding the pistol shooting kinematics, which resulted in Study #2.

A recent paper by Blauberger et al. (2021) described a method to extract the stride parameter ground contact time from inertial sensor signals in sprinting. The study involved a sample of five elite athletes and used kinematic sensor devices on their ankles. The participants performed 34 maximum on the distance of 50 and 100-m. The ground contact time of each step was determined based on features of the recorded kinematic sensor signals. A photo-electric measurement system covering a 50-m corridor of the track was used as a reference system. From a total of 889 steps, 863 were detected correctly which corresponds to 97.08% detection accuracy. The determined ground contact time root mean square error was 7.97 ms. The results of the study indicate smaller ground contact time errors at the beginning and the end of the sprint. The authors concluded that kinematic sensors can provide the temporal parameter ground contact time for elite-level athletes. A study done by Fuchs et al. (2018) explored the topic of proximal-to-distal, i.e. consecutive vs. simultaneous motion sequencing in relation to the reverse punch performed by Wing Chun practitioners. The authors employed a Vicon motion capture system with a sampling frequency of 250 Hz to track full-body motion during strike execution. A general proximal-to-distal initiation of increasing velocities was observed for the pelvis, torso, shoulder, and elbow. In addition, the simultaneous motion sequence did not provide any backswing, which contributed to the shorter overall execution. The two concepts of strike execution provided differences in the range of motion, maximal angular velocities, maximal strike velocity, execution time, and center of body mass movement. The general implications are that the proximal-to-distal scheme provides longer punch reach and higher velocity of the hand. This directly implies larger impact forces. A drawback of this is a longer execution time which provides more opportunities for evasive or counter maneuvers. The aforementioned served as a basis for conceptualization of the work regarding the temporal aspect of karate reverse punch synchronization, which resulted in Study #3.

A study by Jaitner et al. (2015) used a kinematic-sensor-based custom-built system for analysis diagnosis of jumping performance in field conditions. The study employed a kinematic sensor device mounted above the ankle of the participant and examined detection of jump events regarding stance and flight duration for the drop jump using a research sample of 10 athletes and 150 jumps. The take-off and landing instances were determined from the vertical acceleration and a force plate (AMTI) was used as a reference device. Jaitner et al. (2015) report a 94% accuracy of detection of jump events with the respective differences of 3.40±2.97 and 4.87±3.85 ms for stance and flight duration in relation to the reference system. In addition, the authors calculated the reactive strength index from the acquired parameters and reported Bland-Altman 95% agreement of 9.82 to −8.13 ms for stance and 15.02 to −11.40 ms for flight duration. The aforementioned served as a basis for conceptualization of the work regarding the vertical jump height estimation, which resulted in Study #4.

4. Research subject, problems, and aims

Over the last decade, we have witnessed a rapid expansion of kinematic-sensor-based devices that have been widely implemented in the measurement of performance and abilities in different sports. However, some topics remain, whether as completely new areas for future research or simply due to the different research approach that could yield better results.

The subject of this research is the application of kinematic sensors for the measurement and evaluation of sports performance in the four different task categories. The selected individual tasks actually represent examples of a rapid movement task, precision task, complex movement task, and a test of physical, i.e. bio-motor ability. Since the tasks are highly unrelated to each other, they were addressed in four completely separate studies. The first study addressed the problem of selection and categorization of athletes based on the kinematic data acquired in a simple, non-specific, hand tapping test. The second study addressed the problem of tracking movement kinematics during live-fire precision pistol shooting. The third study addressed the problem of monitoring movement kinematics of the karate reverse punch and the relationship of the maximal hand velocity to the temporal structure of the strike. The fourth study addressed the topic of vertical jump height estimation based on the data obtained from a kinematic sensor device placed on the metatarsal part of the athletes' foot. The subject, problems, and aims of each of the studies are presented separately in the following subsections.

4.1. Study #1

Although from the aspect of movement, the system of sport is very complex and diversified, and it can be argued that rapid simple movements are the main form of movement in basically all sports (Verkhoshansky, 1996). Kinematic sensors have been used for the measurement of the kinematics of such movements in different specific situations, such as volleyball spike, baseball pitch, karate punch, etc. (Hansen et al., n.d.; Lapinski et al., 2019; Vuković et al., 2021). In this sense, volleyball is a typical example of a sport where high arm speed is a general prerequisite of successful performance since it is generally required for efficient spiking (Ferris et al., 1995). On the other hand, several studies have shown that kinematic sensors are applicable in the context of classification of player performance and movement classification based on kinematic data (Hansen et al., n.d.; Holatka et al., 2019; Y. Wang, Zhao, et al., 2018) However, a generally under-explored relevant topic is the comparison of players of different age categories in order to provide insight into the unique attributes that can serve as a basis for identification of the individuals that are potentially talented or more capable.

Kinematic sensors provide a possible solution to the aforementioned problem of selection and categorization of the athletes based on the kinematic data acquired in a simple, non-specific test. However, the potential of a kinematic-sensor-based system for discrimination of different groups of participants based on the measurement of rapid hand movement properties in a non-specific test yet has to be determined.

The aim of the research is to determine the potential of a kinematic-sensor-based system to discriminate the different groups of volleyball players and controls in relation to the movement kinematics on a non-specific rapid hand movement task.

4.2. Study #2

The two measures of shooting performance are accuracy and precision. Accuracy can be defined as the extent to which the shots deviate from the center of the target. Precision is the tightens or the size of the group of shots (Johnson, 2001; Kayihan et al., 2013). When combined, the two measures completely describe the performance and skill level of a shooter. Previously published research determined that the shooting ability is compromised by involuntary movement (Lakie, 2010; Pellegrini et al., 2004) with the interval of approximately 1 s before the shot being the most important (Hawkins, 2011). This interval roughly corresponds to the aiming and triggering phases of the shot.

Kinematic sensors can provide a possible solution in relation to the problem of tracking movement kinematics during live-fire precision pistol shooting. This can provide information in relation to the relevant phases of the shot as well as the possible incorrect or excessive movement of the weapon directly related to the accuracy, precision, and overall shooting performance. In short, the results can provide the identification of typical detectable errors. This, in turn, can be used as a basis for real-time biofeedback in this area.

The aim of the research is to determine the relationship between accuracy and precision as relevant measures of shooting performance and weapon kinematics during the aiming and triggering phases of the shot by the application of kinematic sensors coupled with custom-made software.

4.3. Study #3

The reverse punch is a fundamental karate technique. It is executed from a guard position, with the hand opposite to the lead leg (Stull & Barham, 1988). The motion sequencing follows a consecutive proximal-to-distal pattern (Fuchs et al., 2018; VencesBrito et al., 2011), which enables the hand to be imparted with the energy of the preceding motion. This is essential for generating high velocities at the endpoint of the kinetic chain and is found in different striking or throwing-like movements. Such a complex motor action requires optimal intra and inter-muscular coordination (Schmidt et al., 2018). Previously, kinematic sensors have been used to provide information on different phases of high-velocity movements such as baseball pitching and golf swing (Kim & Park, 2020; R. S. McGinnis & Perkins, 2012).

Kinematic sensors can provide a possible solution to the problem of in-field monitoring of movements kinematic and temporal structure of the karate punch otherwise undetectable to human senses, while not compromising the regular training conditions and workflow. Essentially this means that such an approach would provide implicit information on movement synchronization which can then be utilized as feedback in order to improve the learning and training process.

The aim of the research is to determine the differences in the temporal structure of the reverse punch, as measured by multiple kinematic sensors, in relation to the achieved maximal velocity of the hand.

4.4. Study #4

Kinematic sensors have previously been extensively used for the assessment of vertical jump performance. The positioning of the sensor device on the athletes' body in the majority of the studies was at the lower (lumbar) area of the spine (Grainger et al., 2020; McMaster et al., 2021; Picerno et al., 2011) while only several studies used different positioning of the sensor (Garnacho-Castaño et al., 2021; Jaitner et al., 2015). This has a solid basis in the fact that the lower back is the approximate projection of the body center of mass (COM). However, some apparent problems arise from when this location is chosen for sensor placement. For starters, the ante-flexion of the upper body during the eccentric and propulsive phases of the jump causes the change in the absolute alignment of the sensor. Consequently, the projection of gravitational acceleration on different axes of the sensor changes thus making accurate calculation of displacement only from accelerometer data impossible. A way to counter the problem is implementation of somewhat more complicated orient kinematic sensor device to enable calculation of linear acceleration. However, human body is not a rigid object and the joint movement combined with spring like behavior of muscle-tendon units causes the acceleration profile to be distorted. Thus, additional calculations and modeling are needed in order to provide an accurate height estimate.

As a solution to this problem, a vertical jump height estimate can be calculated from data obtained from a single kinematic sensor placed on the metatarsal area of the athletes' dominant foot. As the placement of the sensor is at the end of the kinetic chain, the accurate detection of the time of take-off and landing using only acceleration thresholds should be a straightforward process. Thus, vertical jump height can be accurately estimated using the flight time calculation method.

The aim of the research is to determine whether a kinematic sensor device placed on the metatarsal part of the foot can provide valid and reliable data for an accurate estimate of vertical jump height using the flight time method.

5. Hypotheses

Based on the literature overview and literature analysis as well as on defined subject, problems, and aims of the dissertation a general hypothesis (**Hg**) was defined. In addition, four supporting hypotheses (**H1-H4**) were defined. Each of these hypotheses was addressed in a separate study, and the results have been published in international scientific journals with WoS IF of 1.781 to 3.576.

Hg – Valid and reliable quantification of the kinematic characteristics of human motion can be performed using MEMS kinematic sensors.

H1 - The hypothesis in relation to the discriminate potential of a kinematic-sensor-based system for a non-specific rapid hand movement task (**Study #1**) is that the acquired data will provide a basis for valid classification in relation to performance.

H2 - The hypothesis in relation to the measurement of shooting kinematics (**Study #2**) is that both accuracy and precision will be highly influenced by weapon kinematics as measured by a kinematic sensor.

H3 – The hypothesis in relation to the karate reverse punch movement synchronization (**Study #3**) is that differences exist in the order of the detected events between the punches classified into different groups according to the achieved maximal velocity of the hand.

H4 - The hypothesis in relation to the vertical jump height estimation using a kinematic sensor device placed on the metatarsal part of the foot (**Study #4**) is that such sensor setup will provide valid and reliable results in relation to vertical height calculation in counter-movement and squat jump tasks when compared to the force plate as a criterion device.

6. Measurement method

The individual studies presented in this work employed two different types of IMU sensors, namely LSM6DS33 6 DOF 3D accelerometer/gyroscope (STMicroelectronics, n.d.) and BNO055 9 DOF Bosch orient IMU with combined accelerometer/gyroscope/magnetometer (Sensortec, 2014). Both sensors have been mounted on an Adafruit Feather M0 (Adafruit, n.d.), containing a microcontroller and an integrated Wi-Fi communication module. The device is powered by a Li-Po battery which allows for multiple hours of autonomous measurement. The BNO055 accelerometer measurement range of ±4 g_0 (Sensortec, 2014) while the LMS6DS33 accelerometer measurement range is ±16 (STMicroelectronics, n.d.). The BNO055 provides linear acceleration by removing its gravitational component based on the sensor orientation obtained using a sensor fusion algorithm. For both LSM6DS33 and BNO055 the gyroscope measurement range is ±2000 deg/s. The measurement range of the BNO055 magnetometer is ±2500μT for the z-axis and ±1300μT for both x and y-axis (Sensortec, 2014).

Different modifications of a custom-built sensor device and system were employed for the purposes of each of the individual presented studies. The system is comprised of the main application running on a laptop and a variable number of miniature sensor devices. The main application is developed in the LabView software environment (LabView 2019, National Instruments, Austin, Texas) with the main purpose of signal acquisition, real-time signal synchronization, and control of multiple sensor devices as well as real-time feedback. The main application enables synchronous multichannel recording. The communication with the sensor devices is achieved via User Datagram Protocol (UDP). A general overview of the sensor system and its application is shown in Figure 6.1.

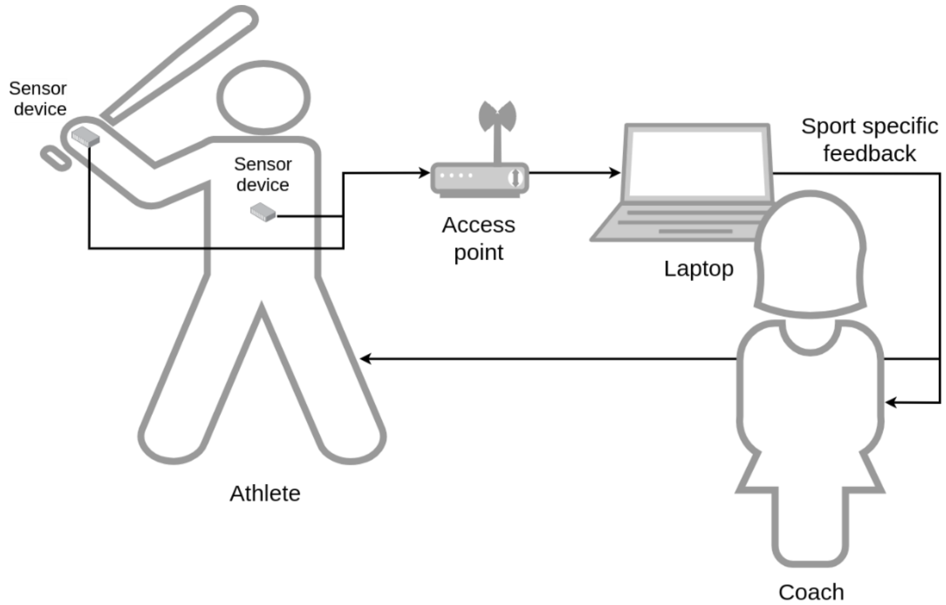

Figure 6.1: Sensor system and application architecture. Sensor devices wirelessly send sensor signals to the application running on a laptop. Results are presented to the coach and the athlete;

Figure 6.2 depicts the three phases of the data follow. In the first phase, the signals are acquired and recorded from one or more sensor devices. Each of the sensor devices is placed on the body of the participant in accordance with the sport-specific requirement of the test. As the result of this phase, raw sensor signals are acquired and stored. Each signal represents an array of consecutive values of the measured physical quantities spaced equidistantly over time in accordance with the predefined system sampling frequency. The second phase is signal processing and data extraction. This phase results in signals filtered with an appropriate filter. Most commonly a Butterworth filter is used in this phase. The cut-off frequency of the filter is dependent on the type of sport-specific test. Consequently, signals of additional physical quantities can be mathematically derived in this phase. After that, motion-specific variables of interest are extracted. In the third phase, data is complemented with test metadata and relevant participant data. After that, the results are statistically processed.

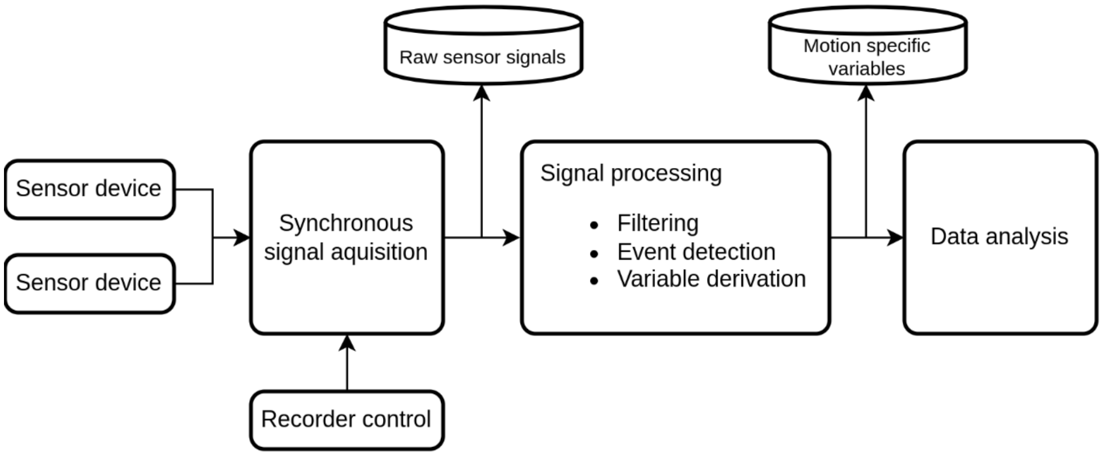

Figure 6.2: The block scheme of the data flow phases; The first phase includes the measurement and recording of the sensor signals during the task execution; The second phase includes signal processing and data extraction of motion specific variables; The third phase includes the data/variable analysis;

Each of the four separate studies in this work used a different approach to the post-processing of the acquired signals as well as a different application/sensor setup in order to provide the relevant research variables. A detailed description of the used methodology is a part of each of the studies presented in the following sections of this work.

7. **Study #1** - Marković, S., Dopsaj, M., Tomažič, S., & Umek, A. (2020). Potential of IMU-Based Systems in Measuring Single Rapid Movement Variables in Females with Different Training Backgrounds and Specialization. *Applied Bionics and Biomechanics*, 2020, Article ID 7919514. https://doi.org/10.1155/2020/7919514

This study addresses the problem of selection and categorization of athletes based on the kinematic data acquired in a simple, non-specific, hand tapping test. The aim of this work is to determine relevant kinematic variables in relation to different groups of participants, that is, to establish the discriminative potential of an IMU-based system for the measurement of rapid hand movement properties. The motivation for this work is to provide the means of comparison of players of different age categories to provide insight into the unique attributes that can serve as a basis for identification and selection.

7.1. Introduction

We have witnessed a rapid development of micro-electromechanical sensor systems (MEMS) in recent years. Consequently, such systems have been applied for everyday purposes as well as in different professional environments (Kos & Umek, 2018a). The system of sport is no exception, as various wearable sensors are regularly used in competition, training, and testing as a means to acquire new or more in-depth information in relation to the different aspects of sports performance. Essentially, this is a reflection of more broad tendencies in relation to the implementation of the new technologies in order to obtain and provide more sensitive and sport-specific information regarding the achieved level of preparedness of elite athletes (Bachev et al., 2018).

Kinematic sensors represent an exemplary case of the MEMS technology which is gaining momentum as a tool used for motion analysis in relation to sports science, as well as sport praxis (Setuain et al., 2016). A kinematic sensor device contains a triaxial accelerometer, gyroscope, and magnetometer built into a miniature wearable device (Staunton et al., 2021). This combination of individual sensors enables the measurement of acceleration and angular velocity as well as calculation of orientation via sensor data fusion for tracking three-dimensional movements with variable levels of precision. In addition, kinematic sensors can be used to obtain information in relation to the temporal characteristics of the analyzed movements (Vuković et al., 2019). In the case of temporal analysis, the measurement precision is dependent on the sampling frequency of the system. Kinematic-sensor-based systems are used in sports training, testing, and competition primarily for the purposes of concurrent and/or terminal biomechanical biofeedback (Kos & Umek, 2018a) and assessment of the state of bio-motor abilities and characteristics relevant for injury prevention and successful performance (Chambers et al., 2015; P. M. McGinnis, 2013; Picerno et al., 2011).

The increasingly fast development of sports science is accompanied by an integrative, multi-structured approach to information gathering in in-field and laboratory testing conditions using a variety of equipment. In order to obtain relevant information in relation to the achieved level of physical preparedness of the athletes during different phases of long-term preparation, multiple measurement methods and technologies are being used (Dopsaj, Umek, et al., 2019). The obtained results can serve as a basis for the purposes of assessment, as well as to calculate the potential of physical abilities and the efficiency of the athletes' performance (Dopsaj, 2015; Tanner & Gore, 2012). In this sense, permanent and periodical monitoring of physical properties expressed in specific conditions of competitive stress (Zarić et al., 2018) as well as in non-specific conditions is achieved by application of basic, i.e. universal, and specific test batteries (Mekhdieva & Zakharova, 2019). The system of sport is very diversified and complex in relation to the movement characteristics. However, it can be argued that rapid simple movements present the main form of movements in basically all sports (Verkhoshansky, 1996). Thus, it is necessary to provide information in relation to this relevant aspect of an athletes' potential, regardless of the specificity of the testing conditions. In this context, volleyball is a good example of a sport that imposes high and complex technical, tactical and physical requirements. This requires high level of development of sport specific skills, as well as basic bio-motor abilities (Fathi et al., 2019) which can be achieved only by application of multidimensional, multistage training which requires constant monitoring.

As aforementioned, different sport settings have provided a field for increased use of kinematic-sensor-based measurement systems for various purposes including technique and performance evaluation (Camomilla et al., 2018), although their application in the measurement of fast hand and arm movements has been fairly limited. The most frequently used researched topic in this context is baseball pitching due to the high number of injury occurrences related to the throwing motion and the need to quantify relevant aspects of performance by measuring the dynamics of the involved segments during peak activity (Lapinski et al., 2009) Although different kinematic patterns are generated, hitting a volleyball and throwing a baseball are similar in terms of overhead functional demand (Rawashdeh et al., 2016). Recent studies employed kinematic sensors for the classification of volleyball players based on evaluation of wrist speed and spiking performance (Hansen et al., n.d.; Holatka et al., 2019) have shown that kinematic-sensor-based systems are applicable in this context as a part of the systems employed for movement classification.

High arm speed is generally required for efficient spiking and is a general prerequisite of successful performance in volleyball (Ferris et al., 1995). Therefore, relevant information regarding the inter-group differences of the kinematic characteristics of rapid arm and hand movements may lead to a better understanding of the stages of athletes' development and potential effects of the training and selection process on their capabilities in this regard. Insight into the attributes unique to the volleyball players can be provided by comparing athletes of different age categories but similar competitive ranking within each category and physically active controls (with no volleyball background) (Lidor & Ziv, 2010). These results can further be used as a basis for the identification of potentially more capable individuals in this regard. Taking all aforementioned into account, a widely used non-specific tapping test commonly used in the testing of basic motor abilities in the non-athlete population, as well as a part of basic test batteries in different sports, was chosen for the purposes of this research.

The aim of this work is to determine relevant kinematic variables in relation to different groups of participants, that is, to establish the discriminative potential of a kinematic-sensor-based system for the measurement of rapid hand movement properties. The motivation for this work is to provide the means of comparison of players of different age categories as to provide insight into the unique attributes that can serve as a basis for identification and selection. As the main contribution, this shows the potential of kinematic sensors for measurement of rapid hand movement properties in a non-specific test which is generally an under-explored relevant topic.

7.2. Materials and methods

7.2.1. The research sample

The research sample consisted of a total of 70 female participants. The overall sample was divided in 3 groups. The first group consisted of physically active controls (age = 22.3 ± 1.9 years, BH = 168.8 ± 5.3 cm, BW = 64.5 ±2.8 kg). The second and third group included the members of the national volleyball team of the Republic of Serbia (age = 24.5 ± 3.5 years, BH = 186.7 ± 4.2 cm, BW = 75.6 ± 2.6 kg) and national-level young volleyball players (age = 16.8 ± 1.8 years, BH = 180.4 ± 6.5 cm, BW = 71.1 ± 3.2 kg), respectively.

7.2.2. Measurement methods

The kinematics of a rapid hand movement was measured using a standard hand tapping test which represents a standard in the measurement of rapid movements of the upper extremity (Dopsaj, Umek, et al., 2019; Wells, 1908, 1909). This tapping test consists of lateral alternating hand movement between the two markers which are positioned at the distance of 50 cm on the table in front of the participant. The test was performed with the dominant hand in an upright sitting position. The hand performing the movement was initially placed on the mark at the opposite side, while the non-dominant hand was positioned at the mark on the mid-length of the movement distance, as shown in Figure 7.1(a). When ready, the subject performed a maximally fast movement. All subjects performed 2 pretest trials used for familiarization with the testing procedure. Afterward, each participant performed three test trials separated with a period of at least 3 minutes of rest (Tanner & Gore, 2012). The best result was taken for further statistical processing (Ivanović & Dopsaj, 2013).

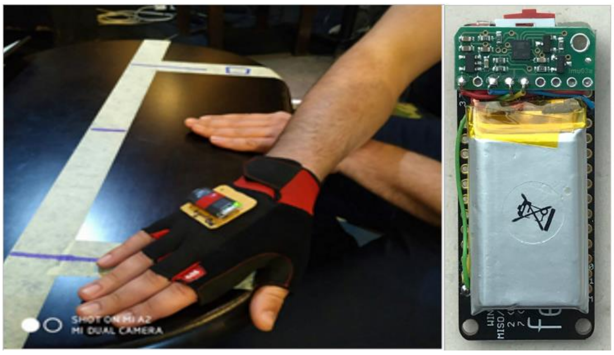

Figure 7.1: The initial position of the subject's hand with the kinematic sensor device attached to the glove (left); A custom-made wireless sensor device (uncovered)

A portable measurement system was developed for the purposes of this research, allowing for a quick setup. The sensor device uses a wireless connection to communicate with the main LabView application. The sensor device includes a MEMS kinematic sensor, a microcontroller with an inbuilt Wi-Fi communication module, all powered by a LiPo battery which allows for several hours of autonomous operation. A custom-made sensor device without a protective housing is shown in Figure 7.1(b). The sensor device is attached to the glove for testing purposes, as shown in Figure 7.1(a). The acceleration in the Y-axis corresponds to the line connecting the markers.

A 3D accelerometer/gyroscope (STMicroelectronics, n.d.) was used on the sensor device; however, for the purpose of our research, we used only accelerometer data. The dynamic range of the accelerometer is ±16 g_0, while the sampling frequency of the system is 200 Hz. The data is continuously sent via a Wi-Fi interface while a custom-made LabVIEW application is used for kinematic variable data acquisition and acceleration signal processing.

In order to process the acceleration signal, a custom-made LabView application (LabView 2019, National Instruments, Austin, Texas) was used. UDP packets containing accelerometer samples are received by a LabVIEW application receiver module. The acceleration signal is filtered using a low-pass Butterworth filter (order = 5, f_{cof} = 40Hz). The onset of the motion was detected when the absolute acceleration exceeded 1.15 g_0 after which the relevant variables in the movement kinematics were automatically detected. Automatic threshold and peak detection are implemented using predefined SubVIs provided by National Instruments for both AY and abs (A), thus providing the magnitude and/or location of the relevant kinematic and temporal variables. Acceleration gradient variables were detected using the peak detector SubVI on the signal obtained by derivation of the acceleration over time.

7.2.3. Variables

In order to define the relevant kinematic and temporal characteristics of the movement the following variables acquired from the processed hand acceleration signal were used:

- t1 [s]- the time from the start of the movement to the first tap of the hand;
- t2 [s] - the time from the first tap to the second tap of the hand;
- A1 [g_0] - the maximal acceleration;
- A2 [g_0] - the maximal deceleration;
- GA1 [$g_0 \cdot s^{-1}$] - the maximal acceleration gradient;
- GA2 [$g_0 \cdot s^{-1}$] - the maximal deceleration gradient;

It should be noted that all acceleration-related variables were measured in the first part of tapping, prior to the first tap. The examined variables and the time frame of events are shown on a typical example of the acceleration signal (Figure 7.2).

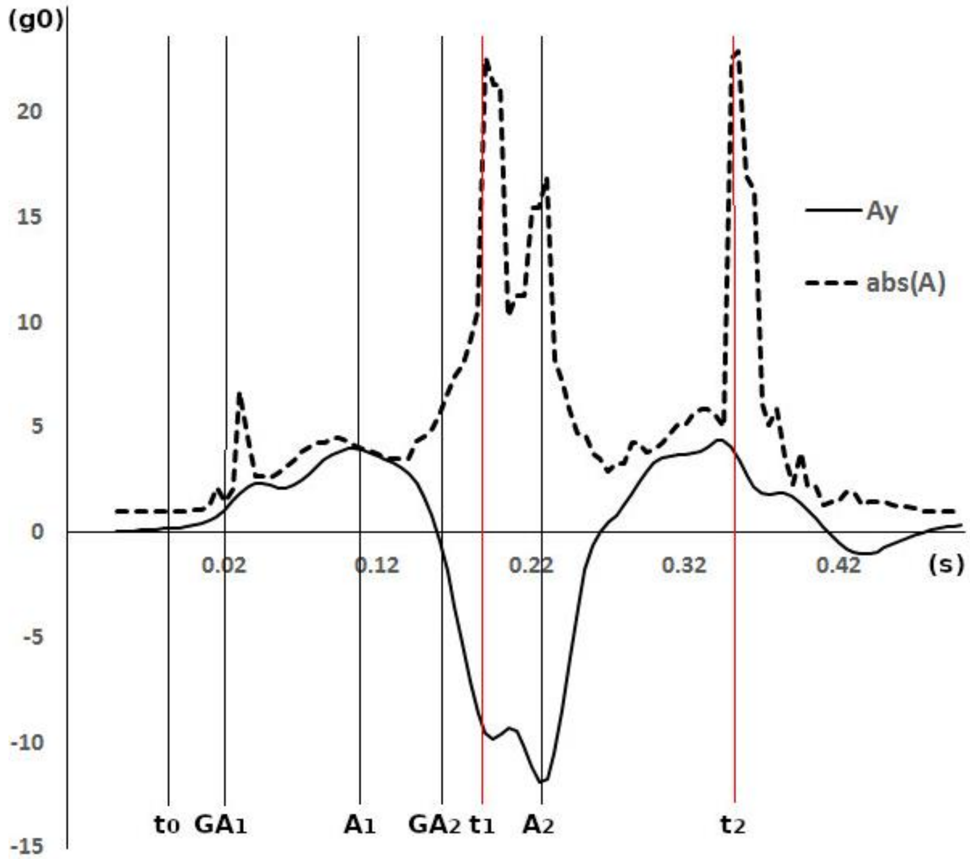

Figure 7.2: Absolute acceleration (abs) and acceleration in the Y (dominant) axis with the time frame of relevant events; The detected temporal and kinematic variables are shown;

7.2.4. Statistical analysis

For the purposes of this work, all variables were processed using descriptive statistical analysis in order to determine relevant measures of central tendency, data dispersion, and range (mean, StDev, SEM, cV%, Min and Max) for the respective subsamples. The normality of the distribution of the results was determined by the application of the nonparametric Kolmogorov-Smirnov goodness-of-fit test (K-S Z). The position of centroid group location, as a group standardized multivariate score, and the structure of the extracted functions and group differences were defined by discriminant analysis. The level of statistical significance was defined based on the criterion $p \leq 0.05$ (Vincent & Weir, 2012). All data analyses were conducted using Excel 2013 and IBM SPSS v23 statistical software.

7.3. Results and discussion

The results of the descriptive statistical analysis of the relevant kinematic variables, as well as the results of the nonparametric one-sample Kolmogorov-Smirnov test in relation to the examined groups, are shown in Table 7.1.

Table 7.1: Basic descriptive statistics of the examined variables in relation to the research subsamples with the results of the One-Sample Kolmogorov-Smirnov Test

	N	Mean	S_EM	StDev.	cV %	Min.	Max.	K-S Z	Sig.
Control									
t1 [s]	22	0.23	0.01	0.03	14.20	0.19	0.29	0.611	0.849
t2 [s]	22	0.43	0.01	0.05	12.50	0.34	0.54	0.741	0.642
A1 [g_0]	22	3.87	0.25	1.17	30.23	2.02	6.23	0.351	1.000
A2 [g_0]	22	8.33	0.44	2.06	24.75	5.34	12.24	0.713	0.689
GA1 [$g_0.s^{-1}$]	22	70.94	5.21	24.42	34.42	36.00	122.13	0.834	0.491
GA2 [$g_0.s^{-1}$]	22	211.73	20.31	95.27	45.00	84.34	485.88	0.961	0.314
Voll_Nat_Team									
	N	Mean	S_EM	StDev.	cV %	Min.	Max.	K-S Z	Sig.
t1 [s]	17	0.21	0.01	0.03	13.92	0.17	0.26	0.590	0.877
t2 [s]	17	0.40	0.01	0.04	9.63	0.37	0.50	1.190	0.117
A1 [g_0]	17	3.88	0.21	0.88	22.63	2.17	5.32	0.563	0.909
A2 [g_0]	17	8.35	0.46	1.91	22.88	4.39	12.07	0.440	0.990
GA1 [$g_0.s^{-1}$]	17	57.30	5.81	23.97	41.84	23.59	109.81	0.433	0.992
GA2 [$g_0.s^{-1}$]	17	229.26	17.62	72.63	31.68	142.95	394.64	0.775	0.586
Voll_Youth									
	N	Mean	S_EM	StDev.	cV %	Min.	Max.	K-S Z	Sig.
t1 [s]	31	0.24	0.00	0.03	11.52	0.18	0.30	0.679	0.746
t2 [s]	31	0.45	0.01	0.04	7.87	0.40	0.52	0.815	0.520
A1 [g_0]	31	3.78	0.18	0.99	26.25	2.48	5.89	0.684	0.737
A2 [g_0]	31	8.94	0.43	2.42	27.04	4.90	14.16	0.725	0.669
GA1 [$g_0.s^{-1}$]	31	72.34	4.63	25.79	35.65	37.88	154.98	0.908	0.382
GA2 [$g_0.s^{-1}$]	31	252.19	17.87	99.51	39.46	96.47	520.85	0.754	0.620

The summary of the canonical discriminant functions and the results of general statistical differences between groups in relation to the examined variables are shown in Table 7.2.

Table 7.2: The Summary of Canonical Discriminant Functions and General Inter-Group Differences

Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	0.641	91.9	91.9	0.625
2	0.057	8.1	100	0.231
Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	0.577	35.492	12	0.000
2	0.946	3.550	5	0.616

The structure matrix of the extracted functions explaining the established general differences between groups is shown in Table 7.3.

Table 7.3: The Structure Matrix

	Function	
	DF1	DF2
t1	0.516	-0.007
t2	0.408	-0.209
A1	0.145	0.654
A2	0.295	-0.412
GA1	0.144	0.318
GA2	-0.056	-0.093

Classification of the group membership in relation to the results of the discriminant analysis of the relevant kinematic variables of rapid hand movement is shown in Table 7.4.

Table 7.4: Classification Results

		Groups	Predicted Group Membership			Total
			Control	Voll_Nat_Team	Voll_Youth	
Original	Count	Control	9	5	8	22
		Voll_Nat_Team	2	12	3	17
		Voll_Youth	5	1	25	31
	%	Control	40.9	22.7	36.4	100
		Voll_Nat_Team	11.8	70.6	17.6	100
		Voll_Youth	16.1	3.2	80.6	100

The graphical representation of the centroid position of the examined subsamples in relation to the relevant functions based on the kinematic variables of rapid hand movement is shown in Figure 7.3.

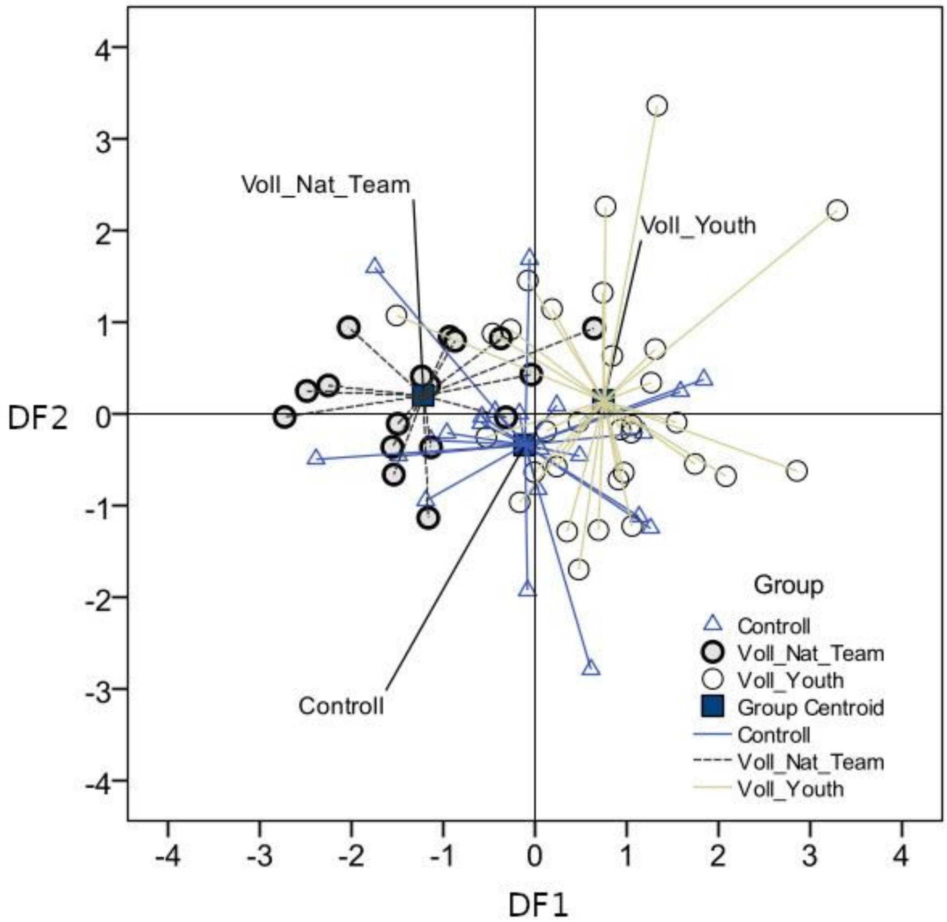

Figure 7.3: The graphical representation of the centroid position of the examined subsamples

Based on the results of the descriptive statistical analysis, it was determined that the coefficient of variation is in the range from 7.87 to 45.00 for t2 in Voll_Youth and GA2 in control samples, respectively, which implies that the examined kinematic variables of rapid hand movement have acceptable variation. The examined variables are normally distributed on a general level as shown by the Kolmogorov-Smirnov goodness-of-fit test (Table 7.1). The results of Box's test of equality of covariance matrices have shown that the multiple distributions of the examined groups are similar on a statistically significant level ($M = 78.488$, $F = 1.605$, $p = 0.008$). On the basis of the aforementioned, it can be argued that the obtained results belong to the same measurement area due to the fact that they are normally distributed and have average homogeneity (Perić, 2003). Thus, they can be considered representative for further scientific interpretation.

Two functions, DF1 and DF2 were identified by the discriminant analysis. These functions explained 91.9 and 8.1% of the variance, respectively. It was determined that DF1 is statistically significant ($p \leq 0.000$). The DF1 function is made of the variables t1 and t2, while the function DF2 is composed of the variables A1, A2, GA1, and GA2. DF2 did not reach significance with a p-value of 0.616 (Table 7.2). This implies that the established differences between the examined subsamples originate from the variables in the first function DF1. The centroid positions of the control, Voll_Nat_Team, and Voll_Youth group in relation to the DF1 function are -0.112, -1.220, and 0.748, respectively (Figure 7.3). The presented results show that the Voll_Nat_Team group centroid position is shifted -1.968 and -1.108 standard deviation values from the Voll_Youth and the control group, respectively, in relation to DF1. The established difference between the control group and the Voll_Youth group is -0.860. No significant difference was found between the observed groups in relation to the second discriminant function (DF2). Thus, in relation to this function, the centroid positions of the groups in relation to this function are similar, as shown in Figure 7.3. The variables that show the greatest discriminative value among the groups represent the temporal characteristics of the rapid hand movement, that is., the time elapsed between the onset of the movement and the first (t1) and second (t2) tap, as shown in Table 7.3.

In relation to the efficiency of the kinematic-sensor-based measurement system regarding the discrimination of the examined sub-samples based on the kinematic characteristics relevant for the rapid hand movement, it was determined that the classification accuracy was 65.7% overall. The highest level of classification accuracy (80.6%) was determined in the subsample of young volleyball players (Voll_Youth). On the other hand, the players in the control group were classified with the lowest accuracy (40.9%). 36.4 and 22.7% of the control group were classified in the subsamples Voll_Youth and Voll_Nat_Team (respectively) in relation to the kinematic characteristics of rapid hand movement, as shown in Table 7.4. For the subsample Voll_Nat_Team, the discriminative efficiency was 70.6%, or 88.2% when taking into account the participants classified in the Voll_Youth group.

The discriminative nature of the obtained results indicates the applicability of kinematic-sensor-based systems for the purposes of assessment, monitoring, and even selection of athletes. Overall, the presented results support the use of kinematic sensors as a tool for the measurement of rapid movement kinematics.

7.4. Conclusion

This work aims to establish the discriminative potential of kinematic-sensor-based systems regarding the detection of the variables/characteristics of single rapid movements in females with different training backgrounds and specializations. Therefore, important kinematic variables, i.e. movement properties, were examined in relation to different groups of participants. The kinematic variables were measured using a standard hand tapping test on a test sample that included a total of 70 female participants. The overall sample was divided into 3 subsamples, of which one included physically active controls, while the other two consisted of the members of the Republic of Serbia national volleyball team and national-level young volleyball players, respectively. The discriminant analysis was used in order to define the centroid location, as a group standardized multivariate score, as well as the structure of the extracted functions and group differences between the respective subsamples. Two functions, DF1 and DF2 were identified by the discriminant analysis. These functions explained explain 91.9 and 8.1% of the variance, respectively. The differences between the examined subsamples originate from the variables grouped in extracted function DF1, which was statistically significant at the level $p \leq 0:000$. Regarding this function, the Voll_Nat_Team group centroid position was moved -1.968 standard deviation values from the Voll_Youth group and -1.108

standard deviation values from the control group. The difference between the control and Voll_Youth groups was -0.860 standard deviation value. The variables of the temporal characteristics of the rapid hand movement are the factors with the highest level of discriminative potential among the groups. These variables are t1 and t2, i.e. the time elapsed between the onset of the movement and the first and second tap, respectively. The findings of this study indicate that kinematic sensors are practically applicable in this context. Thus such systems can be included as a new technology used for the purposes of assessment, monitoring, and selection of athletes.

As the main contribution, this shows the potential of kinematic sensors for measurement of rapid hand movement properties in a non-specific test which is generally an under-explored relevant topic. Further studies should be conducted to determine the applicability of kinematic sensors for sport-specific rapid movement tasks.

8. **Study #2** - Marković, S., Dopsaj, M., Umek, A., Prebeg, G., & Kos, A. (2020). The Relationship of Pistol Movement Measured by a Kinematic Sensor, Shooting Performance and Handgrip Strength. *International Journal of Performance Analysis in Sport*, 20(6). https://doi.org/10.1080/24748668.2020.1833624

This study addresses the relationship of weapon kinematics and handgrip strength to the measures of shooting performance, i.e. accuracy and precision, in live-fire precision pistol shooting. The work aims to establish the relationship between the gun kinematics during the aiming and release phases of the shot and accuracy and precision, i.e. the measures of shooting performance as well as handgrip strength. The main motivation for this work is to provide an innovative approach to the measurement of gun kinematics using a kinematic sensor for the purposes of sport and practical shooting.

8.1. Introduction

Modern shooting and firearms training in general branches in two main directions. The first is related to the needs of police and military structures that have a professional requirement for the competent use of firearms (Vučković et al., 2008). The second clusters all forms of sport shooting. In this category Olympic shooting is dominant, as it is one of the most highly developed, competitive Olympic sports (Mon et al., 2014). There are two measures used for assessing the shooting performance. The first one is accuracy, while the second is precision. However, both of the fore mentioned are highly dependent on the basic techniques learned for shooting which are the stance, grip, sight alignment (aiming), and trigger control (Copay & Charles, 2001). The mean radius of the group of shots is generally considered a primary measure of shooting precision. It is the average of the straight-line distances between the center of the group of shots and each shot (Johnson, 2001). In a more general sense, precision is the size of the group of shots (Johnson, 2001). On the other hand, the extent to which the center of the group of shots is near the center of the target defines shooting accuracy. The sum of points on the target is a common method for measuring shooting accuracy (Kayihan et al., 2013; Vučković et al., 2008).

Previous research has covered multiple relevant aspects that can influence, or induce changes in shooting performance including different physiological, biomechanical, technical, psychological, and physical factors (Anderson & Plecas, 2000; Kos, Umek, et al., 2019; Vučković et al., 2008). Among the physical characteristics of interest for the researchers, one of the most commonly studied has been handgrip strength. Given the fact that it can be easily measured by application of a maximum handgrip test (Dopsaj, Nenasheva, et al., 2019) this is not surprising as this test is a valid, easily administered, highly reliable, status-dependent, and widely used marker of total body strength in adults (Bohannon, 2001). Regarding pistol shooting, the literature is consistent as for the influence of the handgrip strength on shooting performance. The findings suggest the existence of a low (Cohen, 1988), albeit statistically significant correlation between the handgrip strength and shooting performance (Anderson & Plecas, 2000; Kayihan et al., 2013; Mon et al., 2015). This is most likely related to grip stability during the aiming and release phases of the shot and stabilization of the weapon during recoil.

Previous research on elite air pistol and rifle shooters established that the most relevant predictors of shooting performance are the triggering cleanness and hold stability (Hawkins, 2011; Ihalainen et al., 2016). The most sensitive parts of the shot seem to be the pulling of the trigger, i.e. the shot release, and the short interval of aiming (about 1 second) that precedes it (Hawkins, 2011). Physiological tremor, as well as other involuntary movements, affect the shooting ability. These movements can be studied using optical motion capture systems or miniature accelerometers mounted on the gun (Lakie, 2010). A recent study by (Kos, Umek, et al., 2019) has established that miniature kinematic sensors can be used in conjunction with custom-built software for detection of excessive or incorrect gun movement that directly affects both accuracy and precision as well as their combination which defines the overall shooting performance.

The fore-mentioned motivated us to apply new technological, that is sensory, solutions for the measurement of the kinematics of pistol movement at the relevant time intervals before the shot release, as well as to determine their relationship to shooting performance. In order to provide a new perspective on the relationship of the shooting performance measures, i.e. accuracy and precision, and grip strength we re-examined it in the context of different target distances.

This work aims to establish the relationship between the gun kinematics during the aiming and release phases of the shot and accuracy and precision, i.e. the measures of shooting performance as well as handgrip strength. Handgrip strength was measured using a standardized isometric handgrip test while gun kinematics were measured using a custom-built kinematic sensor with specially designed software.

The main motivation for this work is to provide an innovative approach to the measurement of gun kinematics using a kinematic sensor for the purposes of sport and practical shooting. The two main hypotheses of this work are (a) that handgrip strength will correlate to the shooting performance and (b) that shooting accuracy and precision are highly influenced by gun kinematics measured using a kinematic sensor. The main scientific contributions of this work include (a) an innovative approach to the measurement of gun kinematics using a kinematic sensor for the purposes of sport and practical shooting, (b) establishing a relationship of handgrip strength and precision, which is more pronounced in comparison to accuracy, and currently presents an under-researched topic. Since kinematic sensors can provide a measure of gun movement, we are confident that the results presented will demonstrate the potential of such systems for improving the pistol shooting training process and accelerating the acquisition of specific shooting skills.

8.2. Materials and methods

8.2.1. The research sample

This research included a sample of 35 experienced male shooters (Body Height = 183.45±6.21 [cm], Body Weight = 88.52±12.28 [kg], Age = 36.08±12.29 [years], Shooting experience = 6.2±3.7 [years]). For all testing sessions the shooting was performed at the distance of 6 and 15 m.

8.2.2. Measurement methods

The functional capacity of the hand was tested using a standardized handgrip test of isometric hand and finger flexor force (Dopsaj, Nenasheva, et al., 2019). The measurements of handgrip strength were carried out using a strain gauge (All4Gym d.o.o., Serbia). The participants performed the test in a sitting upright position. The hand to be tested was placed in a natural position alongside the body in the abduction of 5 to 10 cm. The participants were not allowed to touch their thighs or any other solid object with the hand or the measurement device during the test. Regarding the handgrip test, all participants performed two pre-measurement trials at sub-maximal intensity for the purposes of familiarization with the test. The hand was alternated. After a minimum of a 5 min break, experimental trials were performed using the trial-to-trial method. The break between individual testing attempts was 3 minutes (Tanner & Gore, 2012). The participants were instructed to use a power grip, i.e. to make the strongest and fastest possible pressure on the device on the researcher's mark. The pressure was maintained for approximately 1-2 seconds. Verbal encouragement was provided during the test trials (Sahaly et al., 2001). Both the non-dominant and the dominant hand were tested twice on the handgrip test in a randomized order and the better result was taken for further statistical processing. The testing of handgrip strength took place 20 min before the testing shooting session.

The precision shooting performance was tested using a Zastava Arms CZ 99 service pistol. A standard International Shooting Sport Federation (ISSF) 25 m circular precision pistol target was used for all shooting sessions for both 6 and 15 m distance. All shootings were performed with 5 rounds per distance. In order to exclude the possible effect of a single outlying shot, we used only the tightest 4 shots, i.e. the shots forming the group with the smallest diameter (M. J. Brown et al., 2013). All participants used a two-handed gun grip and shot from their preferred stance. All shots were performed from the unsupported standing position with no limitation on aiming time. A specialized software SSSE Version 1 (Kos, Umek, et al., 2019) was used to record the shooting performance for each shot. The shooting performance was evaluated regarding precision and accuracy. The mean radius method for the group of 4 best shots was used to evaluate the shooting precision (Johnson, 2001). Shooting accuracy was determined as the sum of the achieved results for the group of 4 best shots (M. J. Brown et al., 2013; Hoffman et al., 1992).

A sensor device on the gun grip was used to measure the movement of the shooter’s arm, as shown in Figure 8.1 – right. The kinematic sensor Y-axis was oriented perpendicular to the frontal plane and parallel to the principal axis of the weapon. Z-axis was oriented perpendicular to the transverse plane, and the X-axis was oriented perpendicular to the sagittal plane. An LSM6DS33 (STMicroelectronics, n.d.) sensor containing a combined 3D accelerometer and gyroscope was placed on an Adafruit Feather M0 WiFi microcontroller (Adafruit, n.d.) with an integrated communication module, powered by a LiPo battery. This setup enabled up to four hours of autonomous operation for the wireless sensor device which has a total weight of 22 grams. The sensor device sampling frequency is 250 Hz, the dynamic range of the accelerometer is +/- 16 g_0, and the dynamic range of the gyroscope is +/- 2000 deg/s. Individual components of the fully assembled sensor device are shown in Figure 8.1 – left and center, respectively. The sensor device serves data via a Wi-Fi interface using UDP. The data is received by a custom-built LabView application (Kos, Umek, et al., 2019) used to capture, process, and store sensor signals as well as to post-analyze the hand movement data. Relevant information about the hand movement was obtained before the shot, specifically in the two selected time windows, which relate to target aiming and shot release. The standard deviations of the acceleration and rotational speed were calculated for the time intervals 1.0-0.1 and 0.1-0.0 seconds before the shot as a measure of weapon movement. The time was obtained from the microcontroller timestamp and the shot was detected as the peak value of absolute hand acceleration.

The study was conducted in accordance with the postulates of the Declaration of Helsinki and was approved by the Ethics Committee of the University of Belgrade Faculty of Sport and Physical Education (02 No. 484-2).

Figure 8.1: Left – sensor device components 6 DoF sensor, microcontroller with Wi-Fi communication module, battery, and encasement; Center – fully assembled sensor device; Right – sensor device mounted onto the bottom of the pistol grip

8.2.3. Variables

To establish the weapon movement, shoot performance, and the functional capacity of the hand multiple variables were used.

The variables used to define the functional capacity of the hand are:

- Maximal isometric muscle force (F_{max}), that is maximal handgrip strength, of the left hand (HGL), right hand (HGR), and both hands (SUM), all expressed in newton (N);
- Maximal isometric muscle force expressed relative to the body mass of the participant (F_{rel}), that is relative handgrip strength, of the right hand (HGR) and both hands (SUM), all expressed in newton per kg of body mass (N/kg);

The variables used to define the shooting performance were:

- The size of the group of 4 shots defined by their mean radius from the center of the group, i.e. Precision (G_RAD), expressed in centimeters (cm);
- The sum of the results on the target for the examined group of shots, i.e. Accuracy (SUM_R), is expressed as the sum of result on the target for all 4 shots (points);

The variables used to define the movement of the pistol were:

- The standard deviation of the acceleration (SDacc), expressed in g_0 (9.81 ms^{-2});
- The standard deviation of the rotational speed (SDgyr), expressed in degrees per second (deg/s);

All pistol movement variables were calculated for all 3 axes (X, Y, and Z) and in relation to aiming and release phases of the shot, which corresponds to the time intervals of 1.0-0.1 and 0.1-0.0 seconds before the shot.

8.2.4. Statistical analysis

The conducted statistical processing of the results includes the descriptive statistical analysis which provided the following statistics: Mean, Standard Deviation (SD), coefficient of variation (cV%), minimum and maximum (Min and Max, respectively). Pearson correlation coefficient was calculated to assess the relationship of the weapon movement, handgrip strength, and shooting performance variables. The defined α level was 0.05. Microsoft Excel 2013 and IBM SPSS v23 software packages were used for data analysis.

8.3. Results and discussion

The results of the descriptive statistical analysis of the maximal isometric muscle force of the hand and finger flexor muscles, i.e. handgrip strength for the right hand (HGR), left hand (HGL) and both hands (SUM) are presented in Table 8.1. The results are presented as absolute values (Fmax), as well as values relative to the body mass (Frel).

Table 8.1 Descriptive statistics for the variables of handgrip strength in relation to the examined sample of shooters

Descriptive Statistics							
		N	Mean	Std. Dev.	cV%	Min.	Max.
F_{max} [N]	*HGR*	35	561.03	98.49	17.56	389.00	874.00
	HGL	35	542.64	94.15	17.35	400.00	879.00
	SUM	35	1103.67	185.65	16.82	824.00	1753.00
F_{rel} [N/kg]	*HGR*	35	6.36	0.87	13.64	4.62	9.36
	HGL	35	6.16	0.86	13.94	4.64	8.56
	SUM	35	12.52	1.62	12.92	9.25	17.92

Table 8.2 shows the results of descriptive statistical analysis for the measures of shooting performance, i.e. accuracy (SUM_R) and precision (G_RAD). The results are presented as the sum of values of points of impact for all 4 shots for the SUM_R variable and as the mean radius of all 4 shots from the center of the group for the G_RAD variable.

Table 8.2 Descriptive statistics for the variables of shooting performance in relation to the examined sample of shooting sessions

Descriptive Statistics						
Target Distance = 6 m						
		Mean	Std. Dev.	cV%	Min.	Max.
Performance	*SUM_R* [points]	35.88	5.12	14.28	22.00	43.00
	G_RAD [cm]	2.42	1.27	52.53	0.50	5.95
Target Distance = 15 m						
		Mean	Std. Dev.	cV%	Min.	Max.
Performance	*SUM_R* [points]	28.70	7.46	25.98	7.00	41.00
	G_RAD [cm]	5.32	2.92	54.93	0.70	12.52

Table 8.3 shows the results of descriptive statistical analysis for the measures of weapon kinematics during the aiming and triggering phases of the shot, i.e. the time intervals 1.0-0.1 and 0.1-0.0 seconds before the shots, respectively. The results are presented as standard deviation values of the signal acquired from the accelerometer (acc) and gyroscope (gyr) for the selected time interval.

Table 8.3 Descriptive statistics for the standard deviation of the kinematic sensor signals, i.e. weapon movement, for the interval 1.0-0.1 and 0.1-0.0 seconds before the shot

Descriptive Statistics										
1.0-0.1 s										
	Target Distance = 6 m					Target Distance = 15 m				
	Min.	Max.	Mean	Stdev.	cV%	Min.	Max.	Mean	Stdev.	cV%
SDaccX [g_0]	0.008	0.084	0.019	0.013	67.70	0.008	0.043	0.016	0.008	51.64
SDaccY [g_0]	0.006	0.093	0.015	0.013	86.06	0.007	0.031	0.012	0.006	52.59
SDaccZ [g_0]	0.007	0.085	0.014	0.013	92.47	0.007	0.027	0.011	0.004	39.41
SDgyrX [deg/s]	0.704	29.752	2.570	3.838	149.34	0.699	6.559	1.840	1.357	73.76
SDgyrY [deg/s]	0.860	20.493	2.746	2.703	98.44	0.749	5.634	2.231	1.281	57.42
SDgyrZ [deg/s]	0.676	30.322	2.657	3.967	149.34	0.650	3.597	1.665	0.784	47.09
0.1-0.0 s										
	Target Distance = 6 m					Target Distance = 15 m				
	Min.	Max.	Mean	Stdev.	cV%	Min.	Max.	Mean	Stdev.	cV%
SDaccX [g_0]	0.009	0.139	0.027	0.020	75.70	0.009	0.044	0.020	0.010	49.26
SDaccY [g_0]	0.007	0.092	0.024	0.017	73.65	0.007	0.062	0.021	0.013	65.25
SDaccZ [g_0]	0.006	0.071	0.017	0.014	84.16	0.006	0.029	0.013	0.006	49.40
SDgyrX [deg/s]	0.466	8.191	3.350	2.044	61.02	0.453	7.057	2.445	1.316	53.84
SDgyrY [deg/s]	0.770	15.175	3.296	2.562	77.72	0.603	5.416	2.358	1.292	54.79
SDgyrZ [deg/s]	0.358	34.849	3.816	4.772	125.04	0.569	5.788	2.346	1.551	66.13

The correlation of absolute (F_{max}) and relative (F_{rel}) handgrip strength, shooting accuracy (SUM_R), and precision (G_RAD) for the shooting distances of 6 and 15 m are presented in Table 8.4 Statistically significant correlations are marked * for p≤0.05.

Table 8.4 Correlations of handgrip strength and the shooting performance, i.e. accuracy and precision at 6 and 15 m shooting distances

Correlations Handgrip vs Performance						
	Target Distance = 6 m					
	HGR	*HGL*	*SUM*	*HGR*	*HGL*	*SUM*
	F_{max}			F_{rel}		
SUM_R	0.388**	0.396**	0.407**	0.184	0.186	0.197
G_RAD	-0.405**	-0.408**	-0.422**	-0.198	-0.200	-0.212
	Target Distance = 15 m					
	HGR	*HGL*	*SUM*	*HGR*	*HGL*	*SUM*
	F_{max}			F_{rel}		
SUM_R	0.484*	0.423*	0.470*	0.291	0.143	0.231
G_RAD	-0.546**	-0.629**	-0.606**	-0.399*	-0.439*	-0.450*

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The correlation of shooting accuracy (SUM_R), precision (G_RAD), and standard deviation values of the signal acquired from the accelerometer (SDacc) and gyroscope (SDgyr) for the selected time interval and shooting distance are presented in Table 8.5.

Table 8.5 Correlations of shooting performance and the standard deviation of the kinematic sensor signal, i.e. weapon movement, for the time intervals 1.0-0.1 and 0.1-0.0 seconds before the shot

Correlations Performance vs Signal				
1.0-0.1 s				
	Target Distance = 6 m		Target Distance = 15 m	
	SUM_R	*G_RAD*	*SUM_R*	*G_RAD*
SDaccX	-0.414**	0.362**	-0.326	0.520**
SDaccY	-0.318*	0.232	-0.263	0.340
SDaccZ	-0.366**	0.166	-0.300	0.208
SDgyrX	-0.219	0.153	-0.349	0.413*
SDgyrY	-0.310*	0.283*	-0.363	0.462*
SDgyrZ	-0.256	0.224	-0.284	0.489**
0.1-0.0 s				
	Target Distance = 6 m		Target Distance = 15 m	
	SUM_R	*G_RAD*	*SUM_R*	*G_RAD*
SDaccX	-0.557**	0.442**	-0.700**	0.563**
SDaccY	-0.624**	0.412**	-0.564**	0.540**
SDaccZ	-0.519**	0.268*	-0.519**	0.405*
SDgyrX	-0.677**	0.648**	-0.430*	0.682**
SDgyrY	-0.487**	0.509**	-0.534**	0.531**
SDgyrZ	-0.466**	0.390**	-0.518**	0.653**
**. Correlation is significant at the 0.01 level (2-tailed).				
*. Correlation is significant at the 0.05 level (2-tailed).				

The mean values of acceleration (SDacc) and rotational speed (SDgyr) standard deviation in all axes for the selected time intervals and shooting distances are presented in Figure 8.2 and Figure 8.3, respectively. Higher values of the standard deviation of acceleration and rotational speed during the time interval 0.1-0.0 s as well as lower values of the same variables on 6 m, relative to 15 m shooting distance should be noted.

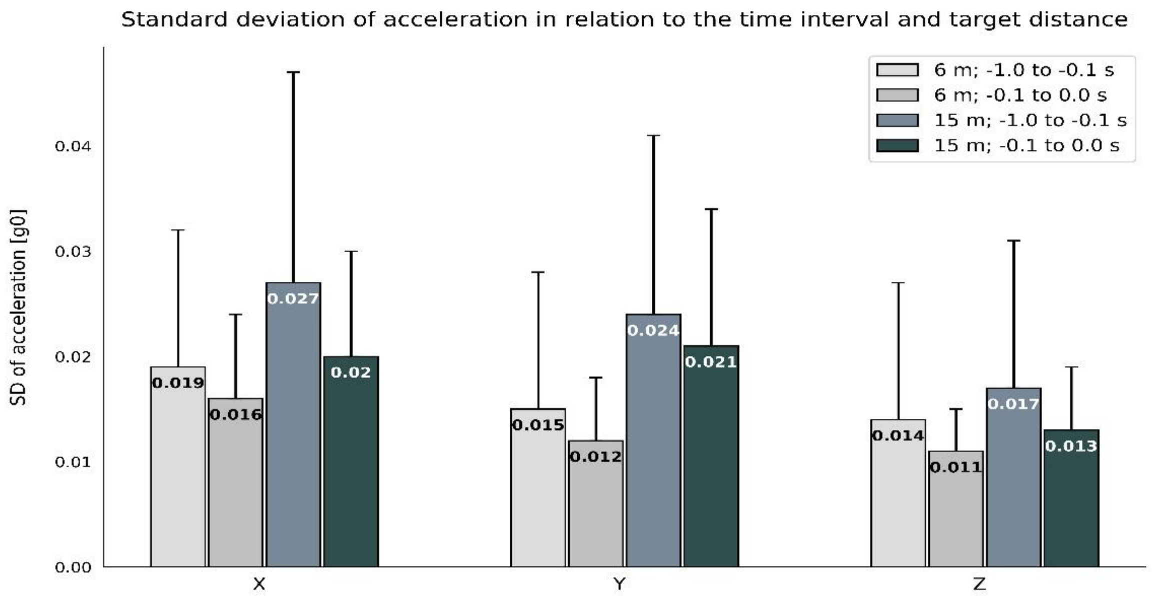

Figure 8.2: Standard deviation of acceleration in relation to aiming and triggering phases of the shot, i.e. the time intervals of 1.0-0.1 and 0.1-0.0 s before the shot for both examined shooting distances

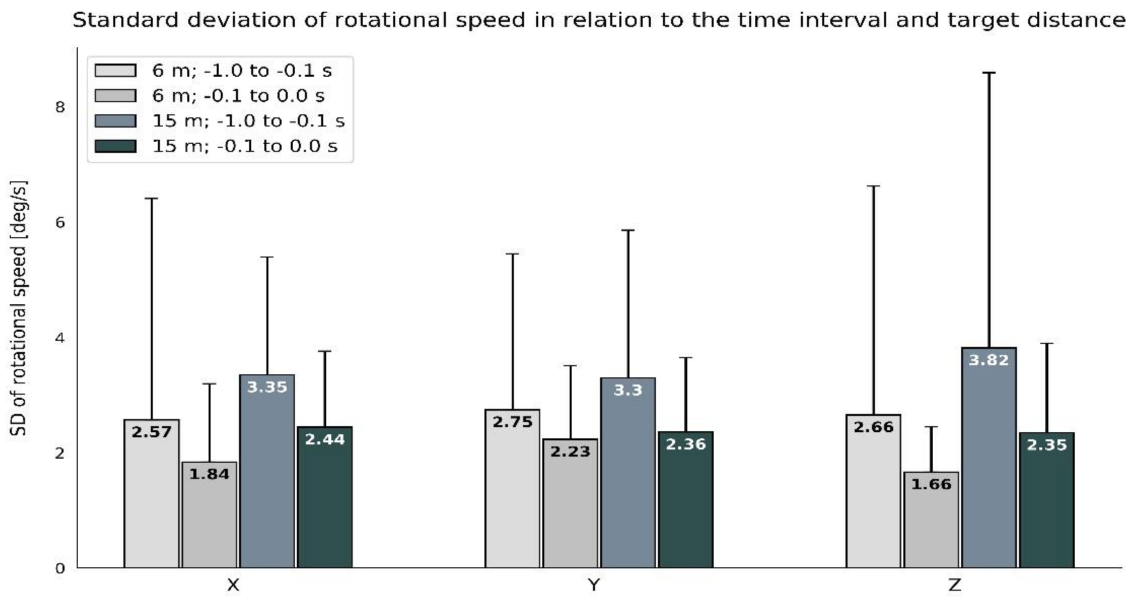

Figure 8.3: The standard deviation of rotational speed in relation to aiming and triggering phases of the shot, i.e. the time intervals of 1.0-0.1 and 0.1-0.0s before the shot for both examined shooting distances

In relation to absolute handgrip strength values of the right, left and both hands and the shooting accuracy at the distance of 6m, a correlation coefficient of 0.388, 0.396, and 0.407 was determined (Table 8.4). The correlations were statistically significant ($p<0.05$). Regarding the 15m shooting distance the correlation of shooting accuracy and the handgrip strength of the right, left and both hands yielded a statistically significant Pearson r of 0.484, 0.423, and 0.470, respectively (Table 8.4), which indicates a more pronounced relationship. No significant correlations were established between the variables of handgrip strength relative to the body mass of the shooter and the accuracy of the shooting (Table 8.4). The fore-mentioned results are in line with the findings of previous studies which have determined the existence of a low to moderate (Cohen, 1988) correlation of absolute handgrip strength and shooting accuracy. A study that included 11 female and 52 male police recruits (Anderson & Plecas, 2000) has established a statistically significant relationship between the shooting score and the dominant hand and combined handgrip strength ($r = 0.38$). Research by (Copay & Charles, 2001) has established a small ($r = 0.27$) statistically significant relationship between the marksmanship score and grip strength. Although the results indicate that the marksmanship score increases with grip strength, the aforementioned study failed to provide a clear threshold of grip strength related to the achieved marksmanship score. The latter is in line with (Orr et al., 2017; Rodd et al., 2010). The authors have concluded that lower handgrip strength may account for the lower shooting scores found in women relative to men. However, multiple other factors may affect the gender-related differences in the shooting score (Anderson & Plecas, 2000). Similar values of shooting score and handgrip strength correlation ($r = 0.242$, $p = 0.01$) were found by (Kayihan et al., 2013), while more recent studies by (Muirhead et al., 2019) and (Orr et al., 2017) found a statistically significant relationship between handgrip strength and shooting score ($r = -0.367$, $p = 0.035$) and ($r >= 0.398$ $p < 0.0001$), respectively.

Regarding the relationship of the shooting precision and the strength of the right, left and both hands this study has established a moderate level of correlation between these variables when considering the 6m shooting distance. The determined Pearson r value was -0.405, -0.408, and -0.422, respectively (Table 8.4). More pronounced correlations were established at the 15m distance. A high (Cohen, 1988), statistically significant, r of -0.546, -0.629, and -0.606 was determined for the right, left, and both hands, respectively (Table 8.4). These findings are consistent with the previous research results that found a high correlation of handgrip strength and shooting precision using the same methodology (Dopsaj et al., 2018). Moderate, statistically significant ($p<0.05$), correlations were determined between handgrip strength relative to the body mass of the participants and shooting precision. The correlation coefficient values of -0.450, -0.439 -0.399 were determined for both hands, left and right hand, respectively. The fact that handgrip strength correlates with both accuracy and precision can be reasonably explained by the fact that handgrip strength is a good indicator of overall body strength in adults (Bohannon, 2001). An addition to this is the fact that hand size significantly correlates with grip strength, with larger hands exerting higher force values (Muirhead et al., 2019). Presumably, larger hands can provide improved conditions for better hand positioning and better alignment of the joints through which recoil will be absorbed as well as lever advantage for trigger pull for any size of the grip of the gun (Anderson & Plecas, 2000). Another factor that can influence the triggering phase and present an advantage for those shooters with stronger hands is the contribution of the index finger flexor muscles to the overall handgrip strength of 23-25% (Ohtsuki, 1981). Thus, shooters with stronger hands can have an advantage when overcoming the resistance of the trigger during the release phase of the shot. Based on all fore mentioned, it can be concluded that shooters with stronger hands will have an advantage in terms of a less prone-to-disturbance and more stable platform for weapon stabilization in the last two phases of the shot, that is the homing-in (Goonetilleke et al., 2009) and release (triggering) phase. This study adds to the results of previous research by providing additional evidence that handgrip strength is a relevant factor that contributes to shooting accuracy. However, a more important finding of this study is the established significant relationships of absolute handgrip strength and shooting precision. The Pearson r values vary from -0.405 to -0.422 for the 6m and from -0.546 to -0.629 for the 15 m shooting distance (Table 8.4). Based on the results it can be argued that, although both precision and accuracy decrease with distance, the handgrip strength is less related to the accuracy, and more related to shooting precision, that is the spread of the results on the target. This difference can be directly attributed to aiming, i.e. the true alignment of the weapon (barrel), gaze, and the center of the target (Goonetilleke et al., 2009). In addition, the correlation of accuracy and precision and handgrip strength determined in this research becomes more pronounced with shooting distance. This indicates that weapon movement control is a more important factor of shooting performance on longer shooting distances. However, pistol shooting is a multidimensional task that integrates psychological, morphological, physiological, and physical aspects (Anderson & Plecas, 2000; Goonetilleke et al., 2009; Kayihan et al., 2013) which points out to need for further research.

The relation of the kinematic variables of weapon movement and shooting performance variables, i.e. accuracy and precision, in the examined time intervals of 1.0-0.1 and 0.1-0.0 seconds before the shot is shown in Table 8.5. It was determined that SDaccX, SDaccY, and SDaccZ are correlated with accuracy (SUM_R) at a statistically significant level, with an r of -0.414, -0.318, and -0.366, respectively (Table 8.5), for the interval of 1.0-0.1 seconds before the shot. Correlation of SDaccX and precision (G_RAD) was moderate ($r= 0.362$, $p<0.05$). At the same distance, correlations of rotational speed (SDgyrY) and both accuracy and precision were statistically significant ($r=-0.310$ and $r=0.283$, $p<0.05$, respectively) (Table 8.5). Regarding the 15m distance and the same time interval of 1.0-0.1 seconds prior to the shot, it was established that precision (G_RAD) is highly correlated with SDaccX ($r=0.520$) and SDgyrX ($r=0.413$), SDgyrY ($r=0.462$), and SDgyrZ ($r=0.489$) at a statistically significant level $p<0.05$ (Table 8.5).

Regarding the interval of 0.1-0.0 seconds before the shot, it was established that accuracy (SUM_R) is correlated with all variables of weapon kinematics at a statistically significant level $p<0.01$. The correlation coefficients indicate a moderate to high correlation of the variables ranging from 0.430, for the SDgyrX at the 15 m distance, up to 0.700 for the SDaccX at the same distance (Table 8.5). When considering the shooting precision (G_RAD) a statistically significant correlation ($p<0.01$) with all variables of weapon kinematics has been determined. The established Pearson r values range from 0.268 for the SDaccZ, up to 0.682 for the SDgyrX (Table 8.5), indicating a moderate-to-high relationship.

The reduction of shooting performance is affected by the changes in postural balance. These are compensated by reciprocal displacement of the kinematic links in the arm which represent compensatory movements. An additional factor to be considered is the muscle tremor (Lakie, 2010; Tang et al., 2008). The rotational speed and acceleration changes can be regarded as a manifestation of involuntary movements that negatively influence the outcome of the shot (Lakie, 2010), as they are directly recorded on the endpoint of the kinetic chain. The present work has established a statistically significant relationship of SDacc and variables of shooting performance, primarily accuracy, for the shooting distance of 6 m and the time interval of 1.0-0.1 seconds prior to the shot release. This corresponds to the homing-in phase of aiming. On the other hand, the variables of rotational speed (SDgyr) are statistically significantly correlated to precision when considering the 15 m shooting distance. In other words, lower values of SDacc variables present an indicator of better accuracy on short shooting distances. Conversely, lower values of SDgyr variables indicate smaller dispersion of the shots thus producing a smaller group on the target, i.e. better precision, on longer shooting distances. As the rotational component of the weapon movement induces the changes in the angular deviation of the shot in relation to the intended point of aim this is manifested fully on longer shooting distances. These findings are in line with (Lakie, 2010) who indicated the possibility that the rotational aspect to hitting the target is of greater importance. Regarding the interval of 0.1-0.0 s prior to the shot release a statistically significant ($p<0.01$) (moderate to high) correlation of all SDacc and SDgyr variables with both shooting accuracy and precision was established. This means that a disturbance of the weapon alignment in the triggering phase of the shot highly influences both of the measures of the shooting performance, whether it is manifested as a change or the rotational speed or acceleration. The fore mentioned is in line with the findings of previous studies (Hawkins, 2011; Ihalainen et al., 2016; Lakie, 2010) which point to the importance of triggering in relation to the shooting performance. The mean values of acceleration and rotational speed standard deviation in all axes for the selected time intervals are presented in Figure 8.2 and Figure 8.3, respectively. A lower magnitude of movement in the aiming phase in relation to the triggering is evident. In addition, all kinematic variables show a lower value on the 15 m distance. This indicates a possible difference in the control of the weapon relative to the perception of the size of the target which varies with distance.

8.4. Conclusion

The present work has established moderate-to-high value of correlations of the variables of the measures of shooting performance and the variables of weapon movement for both time intervals (1.0-0.1 and 0.1-0.0 s before the shot) and shooting distances (6 and 15 m) that were examined. In addition, strong correlations of measures of shooting performance and rotational speed of the weapon indicate high practical importance of the rotational component of weapon movement on the shooting result. This research has established that in the last 0.1 seconds before the shot the weapon kinematics have the strongest relation to the shooting performance. This can be explained by the effect of trigger pull, that is, the disturbance of the weapon in this phase of the shot. The established differences in the correlation of the relative and absolute handgrip strength to shooting performance, show that the use of absolute measure is a superior predictor of performance, which can be related to the constant weight of the weapon. This research has shown that shooting accuracy is less related to handgrip strength when compared to precision. In addition, this is more pronounced with the increase of the shooting distance.

The main scientific contributions of this work include (a) an innovative approach to the measurement of gun kinematics using a kinematic sensor for the purposes of sport and practical shooting, (b) establishing a relationship of handgrip strength and precision, which is more pronounced in comparison to accuracy, and currently presents an under-researched topic. Further studies should be conducted to determine the relation of the variables of shooting performance and weapon movement when considering shooters of different levels of experience, as well as the practical applications of these results for concurrent and terminal feedback in shooting training.

9. Study #3 - Marković, S., Kos, A., Vuković, V., Dopsaj, M., Koropanovski, N., & Umek, A. (2021). Use of IMU in Differential Analysis of the Reverse Punch Temporal Structure in Relation to the Achieved Maximal Hand Velocity. *Sensors*, 21(12), 4148. https://doi.org/10.3390/s21124148

This study addresses the problem of monitoring the movement kinematics of the karate reverse punch and the relationship of the maximal hand velocity to the temporal structure of the strike. The aim of this work is to establish the differences in the temporal structure of the reverse punch in relation to the maximal achieved velocity of the hand using a pair of kinematic sensors. The main motivation of this work is to provide a means for in-field measurement of karate punch movement synchronization.

9.1. Introduction

Karate is a combat sport characterized by high-intensity bouts of activity that impose high physiological and psychophysical demands on the athlete (Baker & Bell, 1990; Chaabene et al., 2012). In order to develop a tactical advantage and score points (Lenetsky et al., 2013) athletes repeatedly perform explosive and technically demanding strikes (Zago et al., 2017). Hand strikes account for more than 80% of all points scored in karate competitions which points out their importance. The most commonly used strike is the reverse punch (Koropanovski et al., 2008; Laird & McLeod, 2009). This can be explained by the fact that the reverse punch is a versatile tool that can be efficiently employed as a direct attack, interception, or counterattack.

As it is a fundamental technique, the reverse punch is taught to all karate practitioners from the very beginning of karate training. It is executed from a guard position, with the hand opposite to the lead leg (Stull & Barham, 1988). The force of the strike is aggregated via the contribution of three components, namely drive off the ground by the legs, rotation of the trunk, and arm muscles action (Filimonov et al., 1985; Lenetsky et al., 2013). In terms of inter-joint coordination, the reverse punch is characterized by a consecutive proximal-to-distal motion sequencing (Fuchs et al., 2018; VencesBrito et al., 2011). This enables the hand to be imparted with the energy of the preceding motion, which is a common pattern found in throwing-like and striking movements (Turner et al., 2011) and is considered to be an essential factor for generating high velocities at the endpoint of the kinetic chain, in this case, the fist. However, the complex structure of such motor action requires optimal intra/inter-muscular coordination (Witte et al., 2005) and sequential control of the series of movements (Tanji, 2001). The temporal structure of the punch represents the invariant aspect of the generalized motor program (Schmidt et al., 2018) governing the execution of the strike. This structure is affected by the motor learning strategies that alter the internal processes defining individual capacity for execution of a motor action after repeated practice (Schmidt & Wrisberg, 2008). Thus, in order to enable an unhampered progression of the training process to the efficient execution of the technique in competition athletes' technique has to be monitored periodically and permanently (Dopsaj, 2015; Koprivica, 2013).

Previous research mainly addressed the kinematics of striking movements, and the underlying neuro-mechanics, using optical 3D motion capture systems and electromyography. However, this is less accessible to the majority of the coaches and athletes as it requires costly equipment and trained personnel to operate it. An additional constraint for regular use of optical motion capture systems (Qualisys, Vicon, etc.) in sport praxis is the time that is required for the system setup in order to do measurements on a single, let alone multiple athletes. As a consequence, the coaches are mainly unable to quantify the changes in the athletes' technique in an objective way and subjective evaluation remains the predominant 'method' in praxis (Saponara, 2017; Sforza et al., 2000). This can lead to conceptual errors and significant misjudgments of the relevant aspects of the athletes' motion.

However, micro-electromechanical sensor systems (MEMS) are becoming more widely implemented for the purposes of obtaining more sport-specific and sensitive information (compared to human observation commonly used in sport praxis) on the level of achieved preparedness in athletes (Bachev et al., 2018; Marković, Dopsaj, Tomažič, et al., 2020). Papers by (Morita et al., 2011; Saponara, 2017) point to the possibilities of the application of kinematic sensors in combat sports. On the other hand, similar solutions developed and implemented in other sport disciplines (Kim & Park, 2020; R. S. McGinnis & Perkins, 2012) have shown that kinematic sensors can be used to provide information on different phases of the movement in baseball pitching and golf swing, respectively. An exemplary overview of the application of kinematic sensors for the purposes of human motion tracking has been presented in (Filippeschi et al., 2017). Based on the fore mentioned, it can be argued that such measurement systems accompanied by adequate software solutions can be used as a means of concurrent and/or terminal feedback to the coaches and athletes (Kos & Umek, 2018a), which can ultimately lead to the improvements in athletes' technical proficiency via objectification of the training methods. In this way, a contribution can be made to the advancement of the competition results. The complexity of the employed kinematic-sensor-based systems varies. The systems used for general purpose applications employ a large numbers of sensors used to cover the anatomical landmark positions, i.e. predefined body attachment points. On the other hand, for specific well-defined movements the number of used sensors is considerably lower. Some of the more important features of the solutions made for specific purposes are easier equipment use, setup and calibration, as well as specific software implementation of the user interface which provides a better user experience. These systems still provide a sufficient level of measurement precision regarding the human movement kinematics, especially for measurement of time-related characteristics of rapid movements. However, it should be stressed out that kinematic sensors can provide sufficient information on the examined movements in terms of detecting the changes in their temporal and overall kinematic structure that are otherwise undetectable to human senses. In addition, the small size of the used sensor devices is effectively has no effect on the regular training conditions and workflow.

The aim of this work is to establish the differences in the temporal structure of the reverse punch in relation to the maximal achieved velocity of the hand using a pair of kinematic sensors. The hypothesis is that a difference exists in the order of the detected events between the strikes that are classified in different groups in relation to the determined maximal hand velocity. The time of occurrence of the relevant events that describe the structure of the punch is defined using rotational speed and acceleration peaks, threshold values, and zero crossings.

The measurement system used in this study is based on kinematic sensors. However, it is not used in a standard way for motion tracking, but for the detection of the sequence of events extracted from the acquired sensor signals. Based on the results of our previous research (Kos et al., 2016b, 2016a; Umek & Kos, 2016), which study in detail accelerometers and gyroscopes inaccuracies and provides guidelines for their use in various applications, including human motion and its kinematic variables, we consider that the possible sensor inaccuracies do not have any relevant effect on the detection of the sequence of kinematic events. The focus is on guidelines for the proper use of inertial sensors in applications that use measured and/or calculated kinematic variables in sports activities. Methods such as bias removal and filtering can only reduce the sensor noise to a certain extent. However, the results of the analysis of the gyroscope and accelerometer inaccuracies on event times confirm that the error in time measurement is in the range of maximally on sampling time. The main result of the proposed methodology is the order of events. Thus, a minor error in the timing measurement does not have an effect on the detected event sequence, i.e. the final result. In accordance with the previous, our standpoint is that the used detection method for the event sequence is not sensitive to the sensor inaccuracies. More details about the influence of sensor inaccuracies on the sequence of detected events can be found in Section 2.3.

The concept that underlies this study is based on a simple, minimalistic, idea of a robust, easy-to-use system that aims to provide feedback regarding the specific key features of the movement which influence its outcome. The proposed methodological approach overcomes the need for a full kinematic analysis, thus reducing the complexity of the used sensor setup while still properly addressing the motion synchronization problem in focus.

The main motivation of this work is to provide a means for in-field measurement of karate punch kinematics. The main contributions of this work include: (a) a new methodological solution for measurement of the temporal sequence of the movement based on the use of kinematic sensors as a means for motion sequence acquisition, implicitly considering the synchronization of movement sub-elements detected by the time of occurrence of the kinematic events in the signal; (b) a more in-depth explanation of sensor inaccuracies showing their insignificant effect on the temporal sequence acquisition based on the events extracted from kinematic variables of sensor signals; (c) determining the inter-group differences on the temporal structure of the movement based on a performance measure, in this case, the maximal hand velocity; (d) providing an initial model of the fore mentioned temporal structure of the movement using the new methodology.

9.2. Materials and methods

9.2.1. The research sample

The research sample included a total of 14 national level and elite karate competitors (kumite) (body height: 1.85 ± 0.03 m; body mass: 81.33 ± 5.03 kg; age: 20.33 ± 2.15 years; training experience: 7.23 ± 2.36 years). The participants performed a total of 165 strikes across several testing sessions which took place according to the availability of the athletes in the interval May–November 2019. As a consequence, individual testing sessions were done in different phases of the yearly training cycle, thus adding to the variability of the results due to the performance changes of each individual resulting from the applied training methods.

Prior to the actual testing, all participants performed an individual warm-up for the duration of 15 min. After that, each of the participants performed 3 test trials which were separated by a 1 min break. For each trial, a single reverse punch was executed. The punch was executed from the Fudo dachi stance (preferred side) with arms in guard position, hips at the angle to the direction of the punch, and back leg bent (Stull & Barham, 1988), thus allowing for full utilization of the entire kinetic chain during the strike (Lenetsky et al., 2013; Loturco et al., 2014). All subjects received instructions to perform the punch with maximal intensity and the highest possible hand velocity. Prior to the testing, all subjects were informed in detail about the measurement procedures and the possible risks and benefits of this research. The study was conducted in accordance with the postulates of the Declaration of Helsinki and was approved by the Ethics Committee of the University of Belgrade Faculty of Sport and Physical Education (02 No. 484-2).

9.2.2. Measurement method

The movement kinematics were measured using the modified version of the measurement system previously used by (Kos, Umek, et al., 2019; Marković, Dopsaj, Tomažič, et al., 2020; Vuković et al., 2021) which features the main LabView application (LabView 2019, National Instruments, Austin, TX, USA) used for signal acquisition and real-time synchronization and control of the sensor devices. The system supports multiple sensor devices and the communication is achieved using the UDP (User Datagram Protocol). In this research, we used two custom-made wireless sensor devices employing a 6 DOF LSM6DS33 (STMicroelectronics, n.d.) 3D accelerometer/gyroscope and a 9 DOF Bosch BNO055 (Sensortec, 2014) orientation sensor, mounted on an Adafruit Feather M0 WiFi micro-controller with a built-in communication module (Adafruit, n.d.), all powered by a LiPo battery and packed in a protective housing. The sampling frequency of the LSM6DS33-based unit was set to 200 Hz while for the BNO055-based unit the sampling frequency was 100 Hz. The measurement range of the accelerometer is up to ±4 g_0 for BNO055 and ±16 g_0 for LSM6DS33. The measurement range of the gyroscope is ±2000 deg/s, for both LSM6DS33 and BNO055. The measurement range of the BNO055 magnetometer is ±1300 μT (x-axis, y-axis) and ±2500 μT (z-axis) (Sensortec, 2014). The BNO055 provides linear acceleration as it excludes gravitational acceleration. This is calculated by subtracting the gravity from the overall acceleration value taking into account the sensor orientation derived by the sensor fusion algorithm from all 3 individual sensors (accelerometer, gyroscope, magnetometer) as defined by the manufacturer datasheet (Sensortec, 2014). One of the sensor units that were used in this research is shown in Figure 9.1.

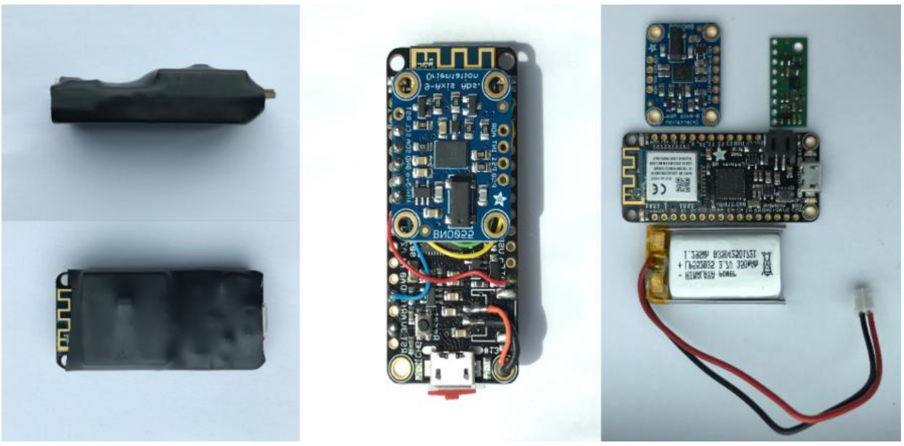

Figure 9.1: Sensor unit in a protective housing, fully assembled, and disassembled (from left to right).

One sensor device was placed on the lower back of the participant, at the level of the lumbar vertebrae IV and V (BNO055), while the other (LSM6DS33) was placed at the dorsal side of the hand, between metacarpal bones II to IV. The sensor on the hand was embedded in a tightly fitting elastic glove, while the one on the back was fixated using an elastic strap (Bedo et al., 2019). Such positioning of the devices was used to provide the most relevant data regarding acceleration and rotational speed of the center of gravity of the striking hand and the body COM (center of mass). As aforementioned, the BNO055 allows for the calculation of the absolute orientation which is why it was considered suitable for monitoring the movement of athletes' body. However, this is achieved with a drawback of a lower sampling frequency. As the hand exerts a more intensive movement, here we employed an LSM6DS33 unit, primarily due to its higher sampling frequency and acceleration measurement range. Figure 9.2 shows the performed movement starting (right), transition (middle), and final (left) position, as well as the positioning of the kinematic sensor device and orientation of the sensor axes.

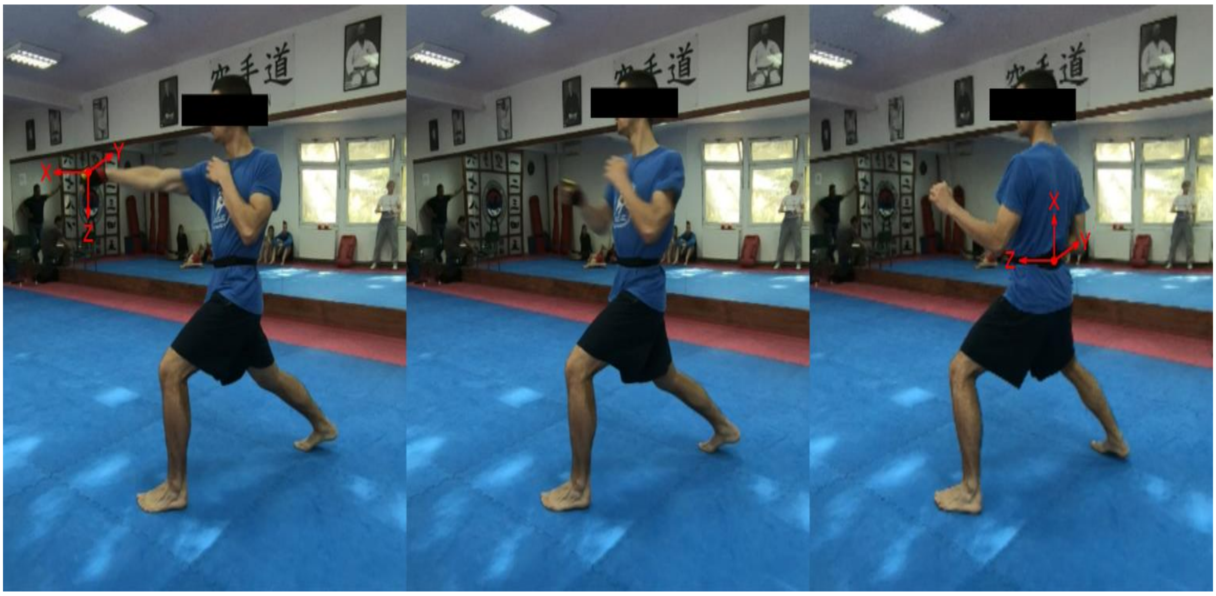

Figure 9.2: The movement start, transition, and end position with the positioning of the sensor devices and orientation of the sensor axes; The figure shows the reverse punch performed from the fudo-dachi stance.

The pre-measurement sensor calibration included bias compensation. The bias measurement averaging interval was 10 s and the bias measurement was performed in a standstill position with the sensor device in a controlled vertical plane. Although the two sensor devices are similar, they have a different kinematic sensor chip installed and a different sampling frequency, as mentioned above. Separate LabView application program loops are used to receive the signal samples from the sensor devices, while the main program loop reads the available data from both sensor devices with a controlled timing cycle of 5 ms. Possible lost data are replaced with their previous values, as UDP does not prevent the data loss due to the packet collisions on a high-loaded ISM band.

In the post-processing phase, the BNO055 signal was used as acquired (Sensortec, 2014) while the LSM6DS33 signal was low-pass filtered using a 5th order Butterworth filter with a cutoff frequency set to 40 Hz. Based on the pilot results, a custom MathCad7 script was developed in order to extract the relevant kinematic events from the signals of acceleration and rotational speed. The script employs threshold and peak detection. Rotational speed and acceleration threshold values were established from the obtained measurement results experimentally. The used threshold values are in line with the ones used regularly in the biomechanical analyses of human movement and range from 3 to 5%. The point where the strike was delivered to the target was identified as the peak in the absolute acceleration of the hand (Kos, Umek, et al., 2019; Marković, Dopsaj, Tomažič, et al., 2020; Vuković et al., 2021). This research considered the timeline of events preceding this point. All events were acquired from the primary and vertical movement axes of the body, i.e. Z and X axes, respectively, as well as from the primary movement axis of the hand, i.e., the X-axis. This is in line with the specific movement pattern of the reverse punch from the front stance as previously described in (Stull & Barham, 1988).

9.2.3. Analysis of sensor inaccuracies

We would like to emphasize that our kinematic-sensor-based measurement system is not used for motion tracking in a classical way. The sensors are not used for an analysis of the movement in space, but to detect the timing of the specific events during the execution of the gyaku-zuki karate punch. The events are defined based on the rotational speed and acceleration selected characteristics as shown in Table 8.1. Events are defined by detecting different signal characteristics: extrema and threshold crossings. The time measurement resolution is primarily limited by the signal processing sampling time, but can also be affected by sensor bias and sensor noise.

While extrema are only sensitive to sensor noise, threshold transition times are sensitive to both sensor noise and bias. The effect of the sensor bias and noise in the measurement of the detected event in Table 9.1 is limited to errors for sample time. A timing error occurs when the amplitude disturbance is greater than the change in the value of the signal between adjacent samples observed at the time of the event. In order to get an accurate answer, we measured the sensor amplitude disturbance s, i.e. both noise and bias, and analyzed the sample-to-sample differences of the signal near the points of all of the detected events defined in Table 9.1.

Although a smaller part of the bias remains after compensation due to bias drift, a greater part of the bias can be removed. The calibration of the sensors in our study was performed prior to attaching the sensors to the athletes' body. The measured gyroscope and accelerometer bias did not exceed 0.1 dps and 3 mg_0, respectively. The actual limitation to the accuracy of the gyroscope and accelerometer is the noise. The typical values of ARW (Angle Random Walk) and VRW (Velocity Random Walk) noise constants are provided by the manufacturer of the sensor. Our sensor noise data are based on measurements of sensor signals in the state of complete physical quiescence of the sensors. All sensor signals are filtered with a low-pass filter (Butterworth, N = 5, f_{cof} = 40 Hz). The shift of the detected events for one sample is influenced by the difference of adjacent noise samples. The noise measurements show that the maximal difference of adjacent noise samples of tested accelerometers does not exceed 5 mg_0, and the maximal difference in adjacent noise samples of tested gyroscopes is less than 0.3 dps.

We calculated the difference of adjacent signal samples near all characteristic points associated with the events in Table 9.1. The sample-to-sample differences of the measured signals in most of the characteristic points are more than ten times larger than the sample-to-sample differences of sensors noise. The results of the analysis of the influence of accelerometer and gyroscope errors on the event times confirm that the error in time measurement practically does not exceed one sampling time. The exception is the error in measuring the time of the motion start event (V_A_D), which in any case occurs as the first event in the chain.

The main result of the temporal analysis in the proposed methodology is the order of the sequence of events. Thus, a minor error in the timing measurement usually does not affect the final result. Therefore, a slight influence of the sensor error on the intermediate result of the measured event times has an insignificant effect on the correct detection of the sequence of events. For this reason, we argue that the method used for the detection of the sequence of events is not sensitive to sensor inaccuracies.

9.2.4. Events

All events that were used in this study are extracted from the signals acquired from the two sensors that were placed on the athletes' back (BACK) and hand (HAND). Temporal events are ranked in the movement timeline. The maximal hand velocity was used as a performance indicator and a basis for group division due to its relationship with the kinetic energy of the strike (Stull & Barham, 1988). The information regarding all the temporal events is shown in Table 9.1. In the used system of abbreviations, (X_Y_Z) X refers to the hand (H), body (B), or vertical (V); the Y character/set of characters refers to the origin, and the Z character refers to the detected instance.

Table 9.1. A detailed description of the events

Abbreviation	Description	Sensor	Signal	Axis	Detection Method
V_A_D	Overall movement start; First vertical disturbance	BODY	lin. acceleration	X	threshold
H_A_S	Hand movement start	HAND	acceleration	X	threshold
V_nA_S	Vertical displacement start; The start of the underweight phase of the movement	BODY	lin. acceleration	X	threshold
B_R_S	Hip rotation start	BODY	rotation speed	X	threshold
B_A_S	Frontal acceleration start	BODY	lin. acceleration	Z	threshold
B_nA_M	Maximal backward body acceleration	BODY	lin. acceleration	Z	peak
V_nA_M	Maximal vertical acceleration of the body in the underweight phase	BODY	lin. acceleration	X	peak
B_A_M	Maximal forward acceleration of the body	BODY	lin. acceleration	Z	peak
V_nV_M	Maximal negative vertical velocity; Start of countermovement stretching phase	BODY	lin. acceleration	X	zero-crossing
B_RS_M	Maximal hip rotation speed	BODY	rotation speed	X	peak
H_A_M	Maximal forward hand acceleration	HAND	acceleration	X	peak
B_V_M	Maximal forward body acceleration	BODY	lin. acceleration	Z	zero-crossing
H_RS_M	Maximal rotation speed of the forearm	HAND	rotation speed	X	peak
V_A_M	Maximal vertical acceleration; Start of propulsion	BODY	lin. acceleration	X	peak
H_V_M	Maximal hand velocity	HAND	acceleration	X	zero-crossing
V_V_M	Maximal vertical velocity; End of vertical propulsion	BODY	lin. acceleration	X	zero-crossing
MaxHandVel	Maximal velocity of the hand	HAND	acceleration	X	num. integration

Figure 9.3 shows a sample of 3 individual strikes performed by the same/different participant with plotted aforementioned temporal events on the corresponding sensor signals. The hand acceleration signal for the dominant movement axis was used for the detection of three events. The first one is the onset of the hand movement (H_A_S) which was detected as the threshold value of 0.5 g_0. The second one is the maximal hand velocity (H_A_M) which was detected using the peak detection method. In addition, the maximal hand velocity (H_V_M) was determined as the point of acceleration zero crossing. In order to include the effect of the rotation of the forearm on elbow extension the maximal rotation of the hand (H_RS_M) was detected as a peak value and was determined from the gyroscope signal in the same axis. The frontal body acceleration was used for the identification of 4 relevant events, namely (B_A_S, B_nA_M, B_A_M, and B_V_M). These events are used for identification of the center of gravity (COG) movement onset, time of maximal backward movement as a possible indicator of implementation of the reactive component to the strike execution, and time of maximal frontal body acceleration, respectively. The threshold value for B_A_S was –0.2 g_0 and B_V_M was detected a priori. The other two events were detected as peak values. The rotational movement of the pelvis was examined using the start of body rotation (B_R_S), detected as the threshold value of 50 deg/s, and maxi-mal body rotation speed (B_RS_M) detected as the peak value in the signal of rotational speed. The vertical acceleration of the body is essential for overall movement kinematics as well as for possible early detection of movement as it reflects the changes in the distribution of weight and body support. Thus, the acquired signal of vertical acceleration was used to identify the time of the slightest disturbance (V_A_D). The absolute value of the vertical acceleration of 0.05 g_0 was used as the threshold for detection. Vertical acceleration start (V_nA_S) was detected when the threshold value of –0.15 g_0 was reached. Maximal negative vertical acceleration (V_nA_M) was detected as the peak negative value prior to the maximal negative vertical velocity of the body (V_nV_M) for which the time of occurrence was known a priori as the acceleration signal crosses the 0. Maximal vertical acceleration (V_A_M) was determined as the peak value and maximal vertical velocity (V_V_M) was detected a priori from zero crossing. The maximal hand velocity (MaxHandVel) is derived from the dominant hand acceleration component by numeric integration. The used sensor signals acquired from 3 trials performed by the same participant in a single testing session are shown in Figure 9.3—left. The used sensor signals acquired from 3 different participants (single testing session) are shown in Figure 9.3—right. The examined temporal events are marked on an exemplar strike both Figure 9.3 left and right.

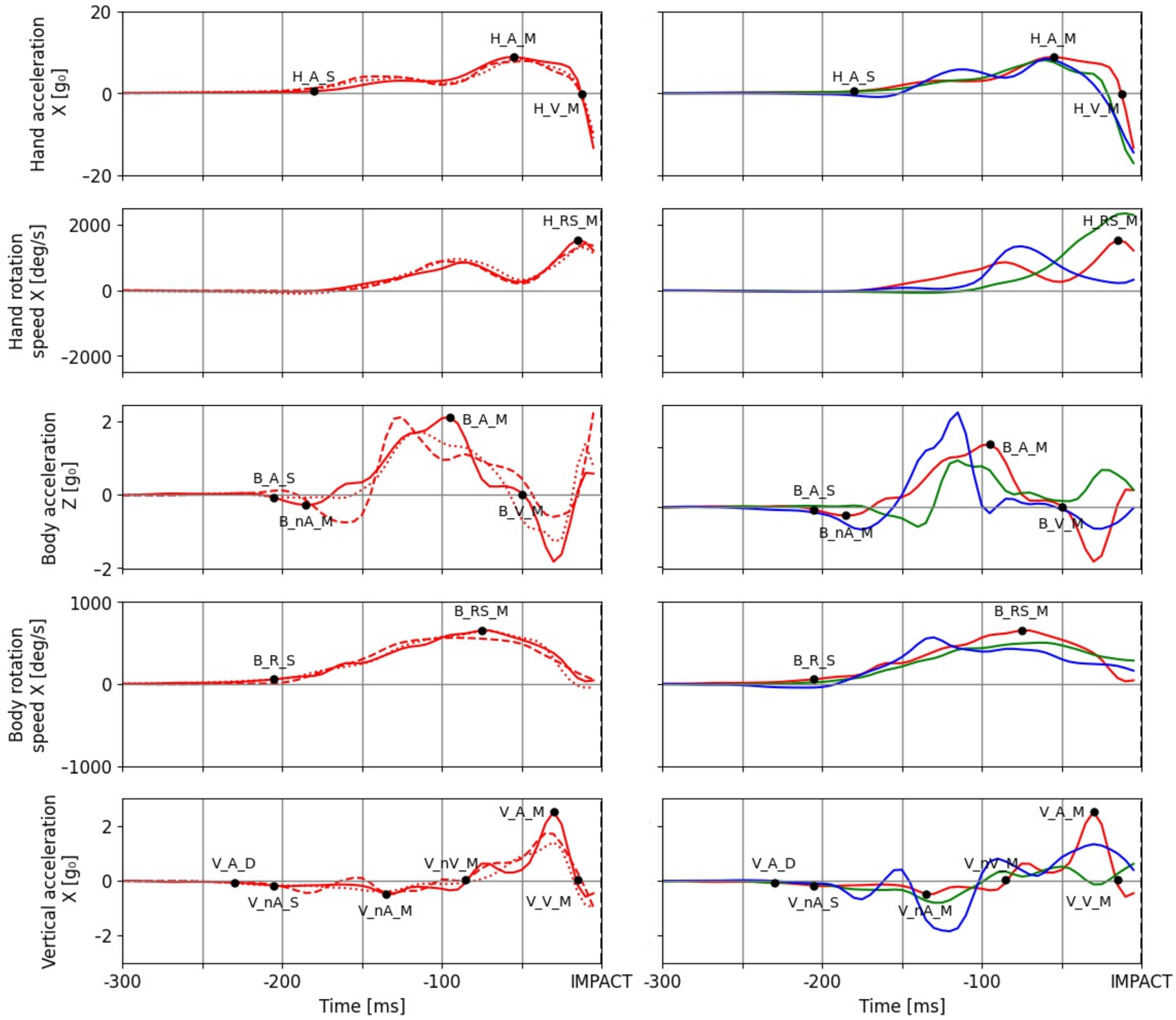

Figure 9.3: The relevant sensor signals with examined temporal events for the same participant (left) and different participants (right); Similar signal pattern for the strikes performed by the same athlete shows a high level of execution consistency; The strikes performed by different athletes show marked differences in signal pattern.

9.2.5. Statistical analysis

In the first step of the analysis, the measures of central tendency and data dispersion were determined for the maximal achieved velocity of the hand. The normality of the distribution of the results was determined using the Shapiro–Wilk goodness of fit test. Subsequently, all strikes were categorized into 3 groups in relation to the achieved absolute value of the maximal hand velocity. The results were scaled to a three-point ordinal scale and converted to nominal values used for further analysis. In order to provide 3 groups similar in size for comparison, the cut-off value for group division was set to $z = \pm 0.5$. The classification methodology was previously described in (Godik, 1988; Vincent & Weir, 2012; Zatsiorsky, 1982).

In the next step of the analysis, all temporal events were transformed into ranks, thus providing a relative measure of the temporal structure of each strike not affected by the inherent differences in the absolute duration of the movement. The median rank of events was provided. In the final step of the analysis, a step-down approach was adopted. General differences in the temporal structure of the punch were determined using a non-parametric Kruskal–Wallis test, for which a $p \leq 0.05$ was considered statistically significant. The Mann–Whitney U test was used for pairwise comparisons, i.e., in order to determine the differences between individual groups. In order to provide more stringent criteria, a $p \leq 0.01$ was considered statistically significant for posthoc tests.

All statistical analyses and data processing were performed using Python3 Pandas and SciPy libraries (McKinney, 2010; Virtanen et al., 2020).

9.3. Results and discussion

Table 9.2 shows the results of the descriptive statistical analysis. The results are presented for the overall sample (ALL). The statistics included in Table 9.2 the mean value (Mean), standard deviation (SD), coefficient of variation (cV), standard error of the mean (SEM), 95% confidence interval (CI), minimum and maximum (Min and Max), as well as the Shapiro–Wilk test statistic and significance (W and Sig.).

Table 9.2. The descriptive statistics for the maximal achieved hand velocity in relation to the overall sample

	Statistics										
	Group	N	Mean	SEM	95% CI	SD	cV	Min	Max	W	Sig.
MaxHandVel [m/s]	ALL	165	6.44	0.08	6.28–6.60	1.02	15.87	3.48	9.35	0.984	0.052

The determined mean value of the maximal hand velocity (MaxHandVel) for the presented overall sample of strikes was 6.64 ± 1.02 m/s, with values ranging from 3.48 to 9.35 m/s. The results are normally distributed ($p = 0.052$, $W = 0.984$) as shown in Table 9.2. On the basis of the achieved MaxHandVel, the overall sample was divided into three groups: FST – fast, AVG – average, and SLW - slow. The appropriate classification method is based on (Godik, 1988; Vincent & Weir, 2012; Zatsiorsky, 1982). The SLW group achieved a median maximal velocity of the hand of 5.72 m/s, while the AVG and FST groups achieved a median maximal hand velocity of 6.37, and 7.11 m/s, respectively. The fore-mentioned results are consistent with the punch velocity data presented in (Beránek et al., 2020), as well as with the previous studies by (Cesari & Bertucco, 2008; Suwarganda et al., 2009), who found a maximal wrist velocity of 7.65 ± 0.86 m/s in Malaysian karate athletes, and 8.21 ± 1.6 m/s in expert karate practitioners, respectively.

In order to avoid the effect of the inherent differences in the absolute duration of the movement all event variables in the strike timeline were rank transformed. In this way, a relative measure of the temporal structure of the reverse punch was provided. Table 9.3 shows the median rank of all of the examined events in relation to the MaxHandVel and group membership. As the maximal hand velocity is an objective performance criterion, the temporal structure of the strikes categorized in the FST group can be considered an initial model of the optimal temporal structure of the reverse punch.

Table 9.3. The median rank of all measured events in the reverse punch timeline in relation to the examined sub-samples

	Event Median Rank							
Group	*V_A_D*	*H_A_S*	*V_nA_S*	*B_R_S*	*B_A_S*	*B_nA_M*	*V_nA_M*	*B_A_M*
SLW	1	4.5	3	4.5	2	6	7	8
AVG	1	3.5	3.5	3.5	3.5	6	7	8.5
FST	1	2	3.5	3.5	5	6	7	8
	V_nV_M	*B_RS_M*	*H_A_M*	*B_V_M*	*H_RS_M*	*V_A_M*	*H_V_M*	*V_V_M*
SLW	9	11	10	12	13	14.5	14.5	16
AVG	8.5	10	11	13	12	14.5	14.5	16
FST	9	10	11	12	13	14	15	16

The results of the Kruskal–Wallis test for general differences of detected events between groups in relation to the maximal velocity of the hand are presented in Table 9.4.

Table 9.4. The general differences in the temporal structure of the reverse punch between the strikes are classified as fast, average, and slow in relation to the achieved maximal hand velocity.

	Kruskal–Wallis Test							
	H_A_S	*B_R_S*	*B_RS_M*	*H_RS_M*	*H_V_M*	*B_V_M*	*H_A_M*	*B_A_S*
Chi-Square	10.31	0.74	0.16	1.36	8.64	7.66	10.37	4.12
df	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Sig.	0.006	0.690	0.925	0.507	0.013	0.022	0.006	0.127
	B_nA_M	*B_A_M*	*V_A_D*	*V_nA_S*	*V_nA_M*	*V_nV_M*	*V_A_M*	*V_V_M*
Chi-Square	2.34	7.25	9.45	0.89	5.16	3.00	0.29	1.12
df	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Sig.	0.310	0.027	0.009	0.641	0.076	0.223	0.866	0.571

Based on the results of the Kruskal-Wallis test, statistically significant general differences between the examined groups regarding the maximal achieved hand velocity were found for the mean rank of V_A_D ($x2 = 0.45$, $p = 0.009$), B_A_M ($x2 =7.25$, $p = 0.027$), H_V_M ($x2 = 8.64$, $p = 0.013$), H_A_S ($x2 = 10.31$, $p = 0.006$), H_A_M ($x2 = 10.37$, $p = 0.006$) and B_V_M ($x2 = 7.66$, $p = 0.022$) as shown in Table 9.4. These results indicates the existence of the differences in the temporal structure of the strike, that is, motion sequencing between the three examined groups.

Table 9.5 presents the results of the Mann–Whitney U test for pairwise differences in the mean rank of individual events between the individual group pairs in relation to the maximal velocity of the hand.

Table 9.5. The pairwise comparisons of the temporal structure of the reverse punch between the strikes classified as fast, average, and slow in relation to the achieved maximal hand velocity

		Mann–Whitney							
		H_A_S	*B_R_S*	*B_RS_M*	*H_RS_M*	*H_V_M*	*B_V_M*	*H_A_M*	*B_A_S*
SLW-AVG	U	1232.00	1349.50	1379.50	1279.00	1275.00	1376.50	1149.00	1183.00
	Sig.	0.272	0.726	0.872	0.424	0.398	0.856	0.100	0.158
SLW-FST	U	1012.00	1410.50	1528.00	1370.50	1079.50	1136.00	1029.50	1216.00
	Sig.	0.001	0.369	0.831	0.257	0.004	0.010	0.002	0.041
AVG-FST	U	1243.50	1493.00	1496.50	1508.00	1245.00	1198.50	1291.50	1524.50
	Sig.	0.060	0.679	0.688	0.745	0.057	0.030	0.105	0.819
		B_nA_M	*B_A_M*	*V_A_D*	*V_nA_S*	*V_nA_M*	*V_nV_M*	*V_A_M*	*V_V_M*
SLW-AVG	U	1359.50	1269.50	1152.00	1396.00	1079.50	1147.50	1336.50	1343.00
	Sig.	0.775	0.377	0.027	0.957	0.031	0.088	0.659	0.569
SLW-FST	U	1314.00	1319.00	1512.50	1404.50	1520.00	1391.50	1481.50	1432.50
	Sig.	0.142	0.143	0.593	0.351	0.789	0.290	0.626	0.287
AVG-FST	U	1375.50	1099.50	1238.00	1449.50	1274.00	1446.00	1555.00	1505.50
	Sig.	0.270	0.005	0.006	0.504	0.080	0.470	0.960	0.647

Based on the Mann–Whitney test results, it can be argued that a statistically significant difference exists between group FST (Mdn = 2) and SLW (Mdn = 4.5) regarding the H_A_S variable (U = 1012, p = 0.001). Earlier hand movement initiation in the overall movement timeline is indicated for the FST group by the calculated H_A_S mean rank of 66.91 and 47.15 for the SLW and FST group, respectively. Difference in H_V_M was statistically significant (U = 1079.50, p = 0.004) in relation to the FST (Mdn = 15) and SLW (Mdn = 14.5) groups. The calculated mean rank values of 64.70 and 47.37 for the FST and SLW groups indicate that the FST group achieves the maximal hand velocity at a time closer to the impact. Statistically significant (U = 1136.00, p = 0.010) difference in B_V_M rank for SLW and FST groups (Mdn = 12, for both) were determined. Based on the mean rank value of 64.57 for the SLW group and 49.25 for the FST group it can be argued that the SLW group reaches the maximal velocity of the body later in the movement in relation to the FST group. Regarding the H_A_M variable, the determined difference in event rank was statistically significant (U = 1029.50, p = 0.002) for FST (Mdn = 11) and SLW (Mdn = 10) groups. The mean rank for the SLW group was 46.42 while for the FST group it was 65.55. This is an indicator of later maximal hand acceleration in the FST group when compared with the SLW group. Statistically significant differences between AVG and FST groups were found in relation to V_A_D (U = 1238.00, p = 0.006; both Mdn = 1) and B_A_M (U = 1099.50, p = 0.005; both Mdn = 8) events. The mean rank value for B_A_M was 65.25 for the AVG group and 48.64 for the FST group, while the mean rank value for V_A_D was 62.64 and 50.98, respectively. Based on the fore mentioned, it can be concluded that the AVG group achieves B_A_M and V_A_D at a later time in the movement timeline.

The initial hypothesis regarding the differences in the timeline of the relevant events, i.e. the temporal structure of the movement in relation to strikes of different velocities has been supported by the presented results. The apparent differences likely originate from the differences in the synchronization of sequential sub-movements which affect the overall movement kinematics (Fuchs et al., 2018). The present study has established that the presented methodology is suitable to detect these differences. Regarding the previous research, it needs to be pointed out that an experimental setup employing just two kinematic sensors was sufficient in order to provide the information related to the temporal characteristics of three key components that contribute to the punch force and velocity, namely drive off the ground by the legs, rotation of the trunk, and action of the arm muscles (Beránek et al., 2020; Fuchs et al., 2018; Hong & Bartlett, 2008; VencesBrito et al., 2011; Zatsiorsky, 2008). These are represented by the events acquired from the vertical and frontal acceleration of the body; the rotational speed of the body; and the acceleration and rotational speed of the hand, respectively. Further research on the reverse punch temporal structure, as well as other related movements, could be beneficial.

9.4. Conclusion

This research used two kinematic sensors mounted on the athletes' body to examine the synchronization of the movement kinematics, which is a new measurement method for this purpose. Based on the presented results it can be argued that the strikes with a high maximal hand velocity show a different pattern of the temporal structure of the relevant kinematic events compared to low and average velocity strikes. This points to the possible differences in the mechanisms that govern the execution of the strike. In addition, the presented methodology has been shown to be suitable for monitoring the movement structure in live practice conditions of repetitive execution of the strike, which affects the acquisition and stabilization of the preferred movement patterns. In this way, the use of kinematic sensors can provide the measurement of movement temporal structure, thus yielding new, more in-depth insights on factors that have an effect on performance.

A limitation to this study is that it does not consider the differences that contribute to the overall kinematics of the punch and originate from the knee, shoulder, and elbow joints. In this sense, the use of a larger number of sensor units may provide a field for further study of the temporal structure of the reverse punch and related movements. However, the contribution of the preceding segments is aggregated toward the endpoint of the kinetic chain. Thus, we consider a two-point setup an optimal solution as it covers the movement of the body COM and hand. The results of this study support that the two sensors allow for a sufficient level of decomposition of the movement in relation to its main contributing factors.

The main contributions of this work include: (a) a new methodological solution for measurement of the temporal sequence of the movement based on the use of kinematic sensors as a means for motion sequence acquisition, implicitly considering the synchronization of movement sub-elements detected by the time of occurrence of the kinematic events in the signal; (b) a more in-depth explanation of sensor inaccuracies showing their insignificant effect on the temporal sequence acquisition based on the events extracted from kinematic variables of sensor signals; (c) determining the inter-group differences on the temporal structure of the movement based on a performance measure, in this case, the maximal hand velocity; (d) providing an initial model of the fore mentioned temporal structure of the movement using the new methodology. Further research should be conducted in relation to the reverse punch temporal structure, as well as other related movements.

10. **Study #4** - Marković, S., Dopsaj, M., Tomažič, S., Kos, A., Nedeljković, A., & Umek, A. (2021). Can IMU Provide an Accurate Vertical Jump Height Estimate? *Applied Sciences (Basel)*, 11(24). https://doi.org/10.3390/app112412025

This study addresses the topic of vertical jump height estimation based on the data obtained from a kinematic sensor device placed on the metatarsal part of the athletes' foot. This work aims to validate the current sensor device and sensor position for VJ height calculation, with the main motivation being to provide a more simple method for measurement of VJ height in field testing conditions.

10.1. Introduction

The vertical jump (VJ) requires the coordination of multiple joints and represents a complex task (Wade et al., 2020). The VJ is related to common sports activities such as acceleration, CODS (change of direction speed), and sprint (Lockie et al., 2011; Loturco et al., 2015; Suarez-Arrones et al., 2020), due to the rapid vertical acceleration of the body in the shortest time interval. The VJ is used in praxis in order to provide information regarding the athletes' training status as well as to inform future training focus (McMahon et al., 2017). It is also heavily used as a means of testing the mechanical properties of the lower limb muscles (Owen et al., 2014). The most widely used jump tests are the squat jump (SQJ) and the counter-movement jump (CMJ). The latter uses the properties of the muscle SSC (stretch-shortening cycle) to more closely resemble the demands of a real-world jumping task. On the other hand, the focus of the SQJ is on the concentric phase of muscle action.

The JH (jump height) is a commonly used measure of VJ performance and an alternative indicator of the explosive capacities of the lower limb muscles (Samozino et al., 2008). Regarding the in-depth analysis of the mechanical characteristics of the lower limb, a predominant method is the use of a force plate (FP). This also enables the JH to be calculated (Linthorne, 2001). However, the use of a FP raises the question of ecological validity in terms of the specificity of the demands of the task. Additionally, a FP is expensive, barely portable, and more-or-less constrained to laboratory settings (Picerno et al., 2011). Thus it is less suitable for in-field use. On the other hand, a FP is commonly used for validation of other devices that are more portable and more regularly used in-field, such as contact mats, photoelectric cells, mobile apps, and kinematic sensors (Glatthorn et al., 2011; McMaster et al., 2021).

A kinematic sensor device typically incorporates an accelerometer, gyroscope, and magnetometer (Staunton et al., 2021). It is a device that falls into the category of MEMS, i.e. micro-electromechanical sensor systems. When supplemented with a sensor fusion algorithm kinematic sensor devices can be used for tracking three-dimensional movements (Marković, Dopsaj, Tomažič, et al., 2020). In addition, the unit can provide precise temporal data in relation to the movement kinematics. The small size of a kinematic sensor device enables it not to affect the athletes' performance, while the low power consumption allows for longer measurement autonomy. In addition, a small battery size further reduces the overall sensor unit size. The combination of the fore mentioned features with low cost and wireless data transmission makes these systems an effective solution for measurement of single or multiple athletes and enables the acquired data to be shared with athletes and coaches instantaneously (Jaitner et al., 2015). There has been an expansion of the application of kinematic-sensor-based systems in the last decade, and these systems have been used for measurement and evaluation of nearly all sports activities (Taborri et al., 2020) with VJ being no exception. Custom and commercial systems have been validated in terms of VJ height measurement and different placements of the unit on the body of the athlete have been used (Borges et al., 2017; Lesinski et al., 2016). The position of the unit on the athletes' body varies from the L5 area (lumbar spine) to positioning on the athletes' ankles (Grainger et al., 2020; Jaitner et al., 2015; McMaster et al., 2021; Picerno et al., 2011).

The equipment used for VJ height assessments in field conditions mainly employs the FT (flight time) calculation method in order to calculate the JH (García-López et al., 2013). In fact, in addition to being the method that is most common for VJ height estimation (Garnacho-Castaño et al., 2021) FT method is valid and reliable (Balsalobre-Fernández et al., 2015; Bosco et al., 1983; Dias et al., 2011; Glatthorn et al., 2011). The same approach to VJ height estimation employing kinematic sensors has been used by (Jaitner et al., 2015). In fact, the FT method is mainly dependent on accurate take-off and landing detection as it employs a basic kinematic equation for JH calculation (Whitmer et al., 2015).

Based on the good results of previous studies by (Garnacho-Castaño et al., 2021; Jaitner et al., 2015) the present work proposes an implementation of a custom-made kinematic sensor device on the metatarsal (distal) area of the foot for the purposes of VJ height estimation by application of FT calculation method. The main motivation for this work is to provide a more simple method for the measurement of VJ height. This work aims to validate the current sensor device and sensor position for VJ height calculation. The main hypothesis is that the presented sensor setup will provide valid and reliable results in terms of VJ height calculation in SQJ and CMJ tasks. The proposed solution contributes by simplifying the take-off and landing detection by placing the sensor close to the endpoint of the kinetic chain. This work presents a simple, cost-effective solution to the common problem of in-field VJ height estimation, which can easily be extended to simultaneous testing of multiple athletes.

10.2. Materials and methods

10.2.1. Participants

The research sample in this study consisted of 13 elite-level volleyball players, all of which were members of the national volleyball team of the Republic of Serbia (Body height = 187.8±4.3 [cm]; Body mass = 75.0±3.87 [kg]; Age = 24.6±3.2 [years]; Training experience = 13.5±3.5 [years]). Prior to the testing session, all subjects were informed in detail about the measurement procedures and the possible risks and benefits of this research. The research was conducted according to the postulates of the Declaration of Helsinki and with the permission of the Ethics Committee of the University of Belgrade Faculty of Sport and Physical Education (02 No. 484-2).

10.2.2. Measurement equipment

For the purposes of this study, we employed a FP (AMTI, USA; sampling frequency 1000 Hz) and a custom-built, kinematic-sensor-based measurement system that was used previously in (Marković, Dopsaj, Tomažič, et al., 2020; Marković, Dopsaj, Umek, et al., 2020; Vuković et al., 2021). The kinematic-sensor-based system is built on top of an Adafruit Feather M0 WiFi micro-controller with a built-in WiFi module (Adafruit, n.d.), and contains 6 degrees of freedom (DOF) LSM6DS33 3D accelerometer/gyroscope (STMicroelectronics, n.d.). The device's overall size and weight are 50x24x10 mm and 22 grams, respectively. The unit is powered by a LiPo battery for up to 4 hours of continuous operation. In this study, only accelerometer data was used. The sampling frequency of the system was set to 200 Hz, with an LSM6DS33 detection range of ±16 g_0 for the accelerometer data. The main LabView application (LabView 2019, National Instruments, Austin, Texas) was used for signal processing, and communication with the kinematic sensor device via User Datagram Protocol (UDP). The signal acquired from the kinematic sensor device, as well as the signal from the FP were low-pass filtered using Butterworth filter (order = 5, f_{cof} = 40 Hz). The calculation of the jump height from kinematic sensor data was performed using the FT method (García-López et al., 2013; Garnacho-Castaño et al., 2021; Glatthorn et al., 2011) by Equation 10.1.

$$h = \frac{{t_F}^2 \cdot g_0}{8}, \tag{10.1}$$

where h is the height of the jump, t_F is the time of flight and g_0 is gravity acceleration (9.81 ms^{-2}). The same method of jump height calculation was used for the FP data (Linthorne, 2001). The threshold value for acceleration was $5g_0$ and the FP ground-reaction force threshold value of zero (±5 N) was used for take-off and landing instances detection (Linthorne, 2001; McMaster et al., 2021).

10.2.3. Flight time measurement

The methodological approach to the JH calculation is summarized in Figure 10.1. In the signal acquisition phase, the raw signal of acceleration is acquired for the X, Y, and Z axis. The signal processing phase combines the filtering of the raw signals, followed by the calculation of the absolute acceleration and event detection. After that, in the final step, the flight time is calculated from the timestamps of the obtained events (take-off and landing) and the jump height is calculated from the determined flight time by Equation 10.1.

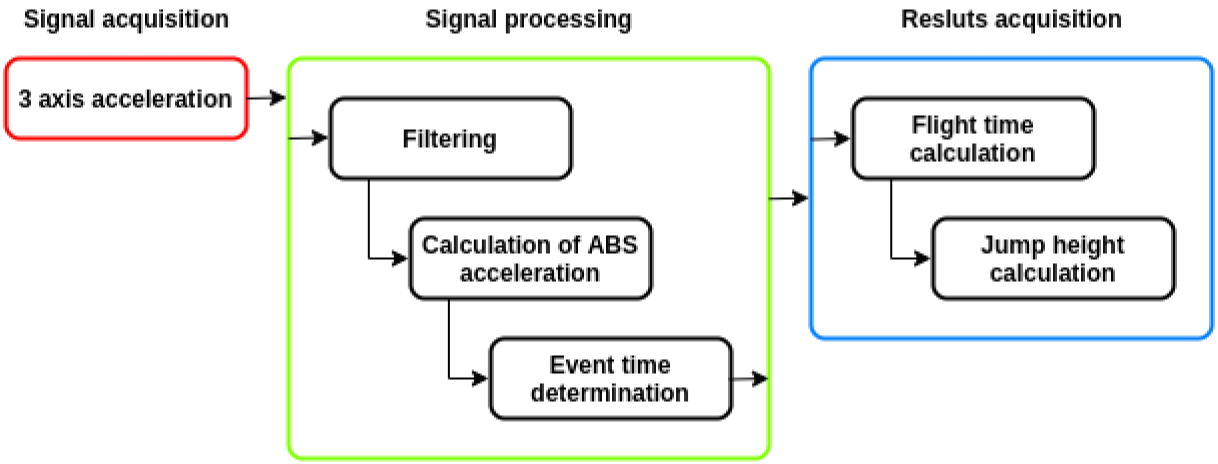

Figure 10.1: The methodology of JH calculation from kinematic sensor data

The accelerometer measures the 3D acceleration vector including gravity acceleration projected on the sensor axes in accordance with the sensor orientation. The measurement of the flight time is based on the detection of take-off and landing events from the acquired absolute acceleration signal. During take-off and landing, pronounced acceleration pulses occur at the selected location of the sensor; the amplitude of both pulses exceeds gravity for the size class. When detecting take-off and landing events, we can therefore choose a threshold value that is much higher than the gravitational acceleration. Consequently, gravity has no significant effect on measuring the time between these two events. An example of the measured acceleration signals with the acceleration threshold marker and the time markers of the detected events is given in Figure 10.2.

Taking into account the sampling frequency of 200 Hz, it should be noted that the analog acceleration signal is filtered in the LMS6DS33 chip with a 100 Hz low pass an-ti-aliasing filterer, as defined in the manufacturer's datasheet [30]. In addition, the acquired signal was filtered using a Butterworth low-pass filter (order = 5, f_{cof} = 40 Hz). A much lower filter cut-off frequency (f_{cof} = 10 Hz) is commonly used in the processing of signals obtained on different human movements, which is aimed towards the elimination of the signal components originating from external factors. However, for the purposes of VJ height estimation, such an approach is inappropriate in relation to the landing phase of the jump in which the athlete's body collides with the surface thus providing an intensive jerk and high acceleration values which can exceed the sensor threshold. Figure 10.2 shows the detection of take-off and landing events using a 5 g_0 threshold on raw and signals filtered using 40 and 20 Hz f_{cof} (red, blue, and black, respectively). Due to the signal being filtered in A/D conversion it can be noted that even raw signal can be used for event detection. However, as the external conditions of in-field measurement may vary additional filtering is implemented. Reducing acceleration signal spectra under 40 Hz introduces errors in detecting the landing event, which can be clearly seen in Figure 10.2.

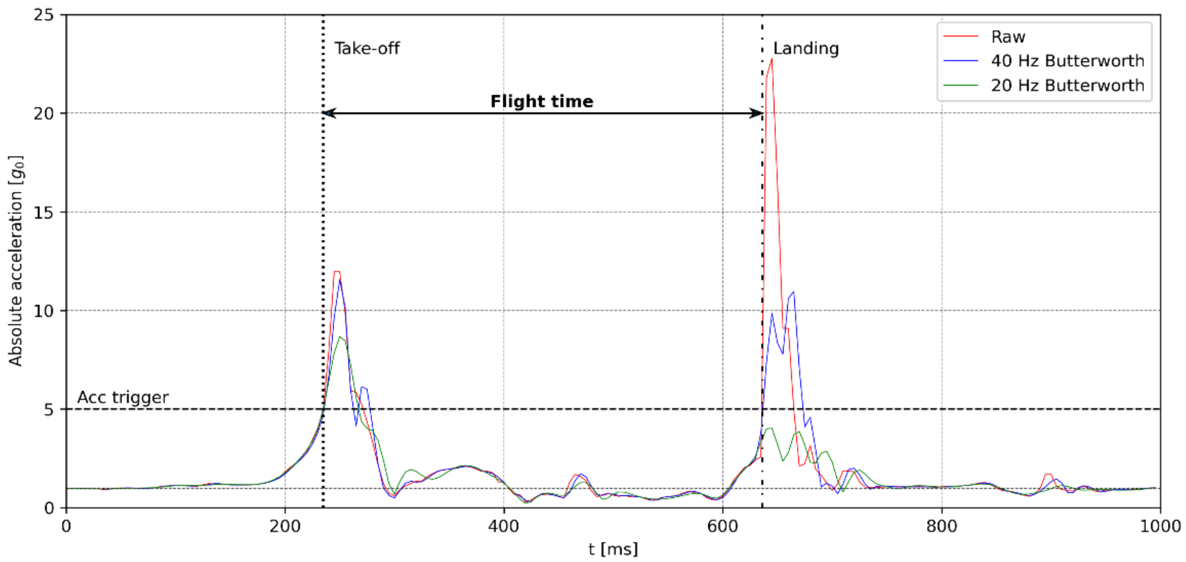

Figure 10.2: Flight time with the effect of different signal filters with detected events and optimal trigger; Take-off and landing events using 5 g_0 threshold are and the acquired raw signal, as well as signals filtered using 40 and 20 Hz cut-off frequency, are shown;

The acceleration threshold value (5 g0) used as a trigger for event detection is optimally set in terms of minimization of the flight time bias and is synchronized to the FP in terms of accurate take-off detection. The error in calculating a vertical jump height is directly affected by flight time measurement error, according to Equation 10.1. Therefore, for a relatively small flight time error, we can use a linearized model to calculate the jump height error, as given by Equation 10.2.

$$e_h = \frac{e_t \cdot t_F \cdot g_0}{4}, \quad (10.2)$$

where e_h is the JH measurement error, e_t is the FT measurement error, t_F is the flight time and g_0 is gravity acceleration (9.81 ms^{-2}).

10.2.4. Measurement procedure

A single testing session was used for determining the VJ height. The session took place in the morning hours, between 9 and 11:30 AM. All athletes were in the postseason period of the yearly training cycle. All participants performed an individual warm-up in the duration of 15 minutes which was supervised by the team strength and conditioning coach. VJ height measurement was performed for the two common jump tasks, i.e. CMJ and SQJ (Linthorne, 2001). The subjects started both tasks standing on the FP shoulder-width apart with their hands on their hips. For the SQJ subjects were instructed to flex their knees to a self-selected position (90-120° knee flexion) which was maintained for 2 seconds (Figure 10.3 - left). After that, subjects performed a jump without a counter-movement. For the CMJ the subjects were instructed to flex their knees to a self-selected position as quickly as possible which was followed by an immediate jump. For both jumps, it was recommended that at takeoff the subjects leave the floor with the knees and ankles extended and land in a similarly extended position (Glatthorn et al., 2011) (Figure 10.3 - middle). The break between the test trials was 30 seconds and the pause between the individual jump modalities was at least 3 minutes [29]. All subjects received instruction to jump for maximum height. The kinematic sensor device was placed in the area of the 2nd to 3rd metatarsal bone, i.e. on the upper distal area of the metatarsal foot as shown in Figure 10.3 – right. A similar placement of the sensor previously used by (Garnacho-Castaño et al., 2021; Jaitner et al., 2015) was employed to simplify the detection of the take-off and landing events.

Figure 10.3: Squat jump - starting (left), take-off/landing position (middle), and kinematic sensor device placement (right)

10.2.5. Variables

The variables in this study represent the VJ height estimated from the data acquired from a FP and a kinematic sensor in the specific tasks of SQJ and CMJ. For determining the validity the combined dataset from two trials performed on the same task was used. These variables are abbreviated as jumpType_device (e.g. CMJ_FP). For the reliability analysis, the dataset was split by trial and the number of trial was added to the abbreviation. Thus, these variables are abbreviated as jumpType_device_trial (e.g. CMJ_KIN_I). All variables used in this research are expressed in cm.

10.2.6. Statistical Analysis

The descriptive statistical analysis was used to provide a basic statistical indicator (Mean, Standard Deviation – SD, Standard Error Mean – SEM, Coefficient of Variation – cV, Minimum – Min, and Maximum – Max). The Shapiro-Wilk test was used to test the normality of the distribution. A paired sample t-test was used to determine the differences in scores in relation to the measurement equipment. Cohen d was provided for effect size, with a value of 0.2, 0.5, and 0.8 considered small, medium, and large effect, respectively (Cohen, 1988). Inter and intra-instrument reliability was assessed using the Intraclass Correlation Coefficient (ICC). Based on the 95% confidence interval of the ICC estimate, values less than 0.5, between 0.5 and 0.75, between 0.75 and 0.9, and greater than 0.90 are indicative of poor, moderate, good, and excellent reliability, respectively (Koo & Li, 2016). In addition, the mean coefficient of variation (McV) was provided (Atkinson & Nevill, 1998). Bland-Altman plots were used to evaluate the discrepancies of the results between the two measurement devices (Bland & Altman, 2010). The level of statistical significance was defined based on the criterion $p \leq 0.05$ [34]. Statistical analyses were conducted using IBM SPSS 23 and Python3 Pandas and SciPy libraries (McKinney, 2010; Virtanen et al., 2020).

10.3. Results and discussion

The results of the descriptive statistical analysis for the calculated JH for both FP and kinematic sensor device, on SQJ and CMJ tasks using the FT method, are shown in Table 10.1.

Table 10.1. Descriptive statistics and normality of the distribution of counter-movement (CMJ) and squat jump (SQJ) height, as estimated based on the flight-time (FT) determined from a force plate (FP) and a kinematic sensor device (KIN).

Descriptive Statistics									
	N	Min [cm]	Max [cm]	Mean [cm]	SEM [cm]	SD [cm]	cV [%]	W	p
CMJ_FP	26	24.83	38.32	30.29	0.67	3.41	11.26	0.957	0.339
CMJ_KIN	26	24.60	39.14	30.11	0.64	3.25	10.78	0.953	0.276
SQJ_FP	26	22.15	32.65	27.36	0.52	2.67	9.76	0.983	0.925
SQJ_KIN	26	19.13	33.16	27.54	0.67	3.43	12.45	0.972	0.684

The results of the validity analysis of the VJ height measurement using a kinematic sensor compared to the FP as a criterion device is shown in Table 10.2. The results that are presented show the calculated mean and standard deviation of JH value for both devices (FP, KIN), results of a paired samples t-test with effect size (t, p, d), mean intra-subject coefficient of variation of the results (McV) as well as the intraclass correlation coefficient (ICC) and Bland-Altman bias and limits of agreement (Bias and LOA respectively).

Table 10.2. Concurrent validity of a kinematic sensor device (KIN) vs. a force plate (FP) for vertical jump height estimation.

Concurrent validity KIN vs. FP		
	CMJ	SQJ
FP (95% CI) [cm]	30.29±3.41 (28.98; 31.6)	27.36±2.67 (26.33; 28.39)
KIN (95% CI) [cm]	30.11±3.25 (28.86; 31.36)	27.54±3.43 (26.22; 28.86)
t test (t, p, d)	(0.897, 0.379, 0.176)	(-0.564, 0.578, 0.111)
ICC (95% CI)	0.975 (0.944; 0.989)	0.921 (0.825; 0.965)
McV [%]	1.896	3.556
Bias (95% CI) [cm]	-0.18 (-0.6; 0.24)	0.18 (-0.49; 0.85)
Lower LOA (95% CI) [cm]	-2.26 (-2.99; -1.54)	-3.14 (-4.3; -1.97)
Upper LOA (95% CI) [cm]	1.9 (1.17; 2.63)	3.5 (2.34; 4.66)

Figure 10.4 shows the discrepancies of the estimated VJ height between a FP and a kinematic sensor device (KIN) for the squat jump (SQJ) as the VJ test modality.

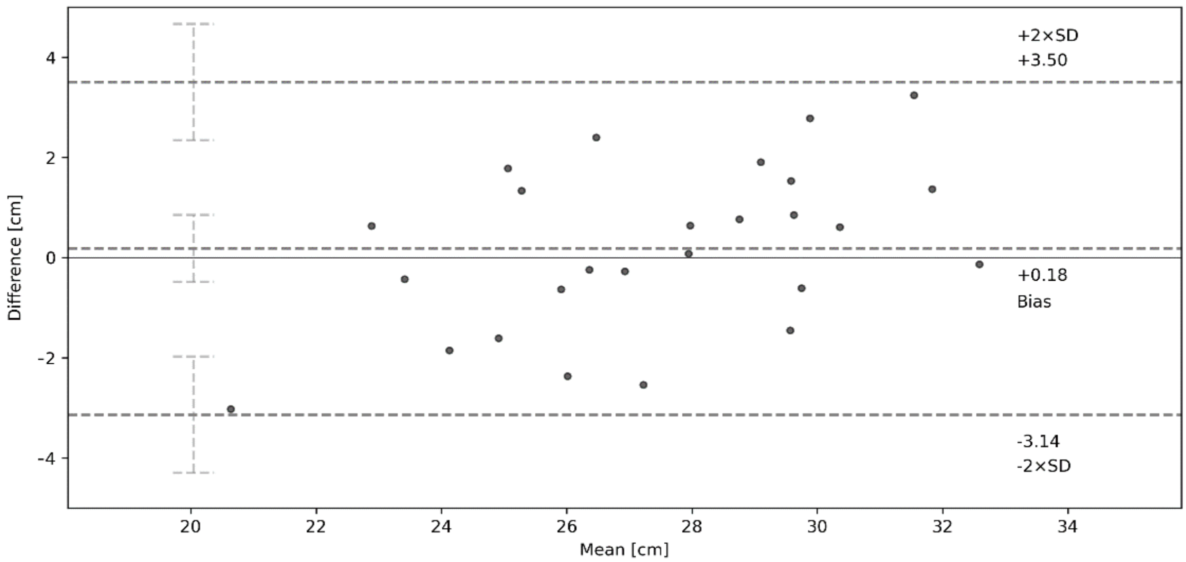

Figure 10.4: Force plate vs. kinematic sensor device measuring SQJ height agreement (Bland-Altman plot)

Figure 10.5 shows the discrepancies of the estimated VJ height between a FP and a kinematic sensor device (KIN) for the counter-movement jump (CMJ) as the VJ test modality.

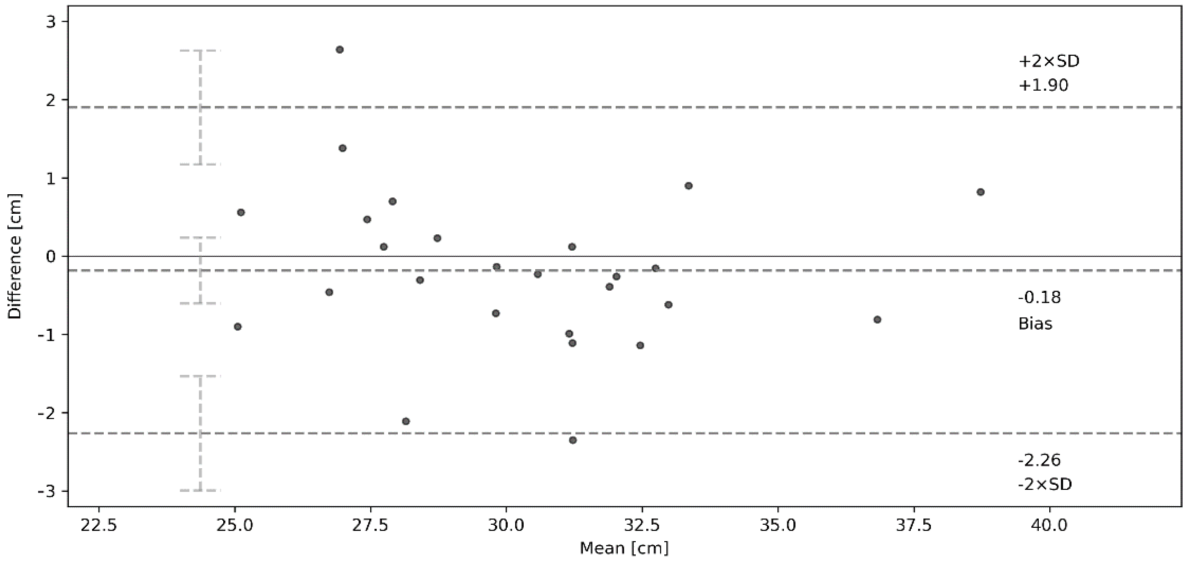

Figure 10.5: Force plate vs. kinematic sensor device (KIN) measuring CMJ height agreement (Bland-Altman plot)

The results of the reliability analysis of the VJ height measurement using a kinematic sensor device on the metatarsal part of the foot are shown in Table 10.3. The results include the calculated mean and standard deviation of JH for two trials, the mean intra-subject coefficient of variation of the results (McV) as well as the intraclass correlation coefficient (ICC).

Table 10.3. Test-retest reliability of a kinematic sensor device (KIN) for vertical jump height estimation.

KIN reliability		
	CMJ	SQJ
KIN_I (95% CI) [cm]	30.46±3.7 (28.45; 32.48)	28.29±3.15 (26.58; 30.01)
KIN_II (95% CI) [cm]	29.75±2.82 (28.22; 31.29)	26.79±3.65 (24.81; 28.77)
McV [%]	4.116	5.933
ICC (95% CI)	0.888 (0.633; 0.966)	0.872 (0.58; 0.961)

The aim of this research was to validate the presented sensor unit and its positioning on the athletes' body in relation to the VJ height estimation for the two commonly used jump modalities, i.e. the CMJ and the SQJ. In relation to the results acquired from the FP, an overall JH of 30.29±3.41 and 27.36±2.67 cm was determined for the CMJ and SQJ. The JH calculated from kinematic sensor data was 30.11±3.25 and 27.54±3.43 cm for the CMJ and SQJ, respectively, as shown in Table 10.1. In relation to the validity of the kinematic sensor device, the results of a paired sample t-test have shown no statistical significance of the differences in the VJ height when compared with the FP for CMJ ($t=0.897$, $p=0.379$) and SQJ ($t=-0.564$, $p=0.578$), with negligible effect size ($d=0.111$ and $d=0.176$

respectively) (Cohen, 1988) (Table 10.2). Excellent level of agreement of the device results for measuring VJ height using the FT method has been shown by the ICC values of 0.921 and 0.975 for SQJ and CMJ (Koo & Li, 2016; Vincent & Weir, 2012). This is further supported by the low McV values of 1.90 % for the CMJ and 3.56 % for the SQJ task. The differences in the calculated JH between the measurement devices have no practical significance as shown by the Bland-Altman systematic bias value of 0.18 cm for SQJ and -0.18 cm for CMJ (Table 10.2). The lower SQJ height results have yielded a higher value of the standard deviation of the differences, thus providing a wider LOA (-3.14 and 3.5 cm) when compared to CMJ (-2.26 and 1.9 cm, for upper and lower LOA, respectively) (Table 10.2). The agreement of the devices for the respective jump modalities is shown in Figure 10.4 and Figure 10.5. In relation to the reliability of the kinematic sensor device for estimation of VJ height, low values of McV (4.12 and 5.93 %) were determined for the CMJ and SQJ, respectively. An intraclass correlation coefficient value of 0.888 has been established for the CMJ. On the other hand, for the SQJ the determined value of ICC was 0.872 (Table 10.3). The presented results indicate a high level of reliability (Koo & Li, 2016; Vincent & Weir, 2012) of the VJ height estimate for both jump modalities. Taken as a whole, the results of this study support a high level of reliability and validity of a kinematic sensor device for the estimation of VJ height using the FT method.

The results of the present study add on top of the findings of (Jaitner et al., 2015), who placed a kinematic sensor device above the ankle in order to calculate the FT of a drop jump (DJ) from vertical acceleration, as well as (Garnacho-Castaño et al., 2021) who estimated VJ height by FT in CMJ and SQJ tasks using a commercial Polar V800 and a stride sensor. In all, the findings show that VJ height can be effectively estimated from accelerometer data only when the sensor is placed on the foot. This approach is an alternative to the frequently used positioning of the sensor on the back of the participant (Grainger et al., 2020; McMaster et al., 2021; Picerno et al., 2011). The main pro of this solution is the simplification of the JH calculation, due to the fact that calculation of the sensor orientation is not necessary in order to remove the vertical acceleration component during the movement of the trunk. In addition, the present study provides the data related to the VJ height estimate in elite athletes using the proposed sensor placement which is lacking (Garnacho-Castaño et al., 2021).

The small size of the used sample and its homogeneity in terms of the VJ height can be considered as the main limitations of this research. In addition, the sensor is mounted on just one foot can possibly be considered a limitation in terms of FT measurement precision. However, this is not supported by the presented results obtained on elite athletes.

10.4. Conclusion

This study has established a high level of concurrent validity of a kinematic sensor device versus a FP for VJ height estimation using the FT method. The sensor positioning on the distal part of the metatarsal area of the foot has shown to provide a high level of agreement between the two systems in terms of the determined FT, that is, the calculated JH. This further implies that the presented approach and sensor setup combination can be effectively used for in-field measurement of vertical jump height. In addition, a high level of kinematic sensor device reliability was determined.

As a general conclusion, it can be argued that a simple kinematic-sensor-based system can provide a portable, lightweight alternative to contact mats and photoelectric cells in relation to the measurement of VJ height in field conditions, as well as that the placement of kinematic sensor device can be an alternative to the position on the athletes back in terms of simplifying the JH calculation.

The main contribution of this work is the simplification of the take-off and landing detection by placing the sensor close to the endpoint of the kinetic chain. In addition, this work presents a simple, cost-effective solution to the common problem of in-field VJ height estimation. Further research should be conducted in relation application of the system on multiple athletes and/or in-game conditions.

11. General conclusion

The development of athletes' skills and bio-motor abilities to a high level is a sequential process that requires multiple adaptations initiated by repeated exposure to whether physical or physiological stress. In order to enable this progression, periodization of the training cycle is used to provide a basis for full summation of the training effects via systematic manipulation of the components of training load. In the long-term process of deterministic management of training, the decision-making is based on relevant and timely information. On the other hand, skill acquisition and short-term management of training benefit from augmented feedback in relation to the relevant motion and/or performance parameters. In any case, the quantification of human motion and performance is essential for data-driven decision making, as opposed to intuition and simple observation.

In relation to its kinematic characteristics, human motion and performance can be quantified by means of quantitative biomechanical analysis, where kinematic analysis using optical motion capture systems serves as a predominant tool. The development of micro-electro-mechanical systems has produced kinematic sensor devices that can be used that operate on inertial principles and can serve as an alternative to the aforementioned optical motion capture. The basic elements of all such systems are kinematic sensor devices that combine an accelerometer, gyroscope, and magnetometer and provide multiple measured and derived quantities. The inertial systems provide several pros when compared to their optical counterparts, with portability, and price being the most important. Their major drawback is related to the lower performance.

The main aim of this work was to determine the potential of kinematic sensors in relation to estimation of bio-motor abilities and measurement of movement kinematics in precision and rapid movement tasks. This was achieved in four separate studies. The first study addressed the problem of selection and categorization of athletes based on the kinematic data acquired in a simple, non-specific, hand tapping test. The second study addressed the problem of tracking movement kinematics during live-fire precision pistol shooting. The third study addressed the problem of monitoring movement kinematics of the karate reverse punch and the relationship of the maximal hand velocity to the temporal structure of the strike. The fourth study addressed the topic of vertical jump height estimation based on the data obtained from a kinematic sensor device placed on the metatarsal part of the athletes' foot.

In relation to the general research hypothesis, the following can be concluded:

H1 - The hypothesis in relation to the discriminate potential of a kinematic sensor based system for a non-specific rapid hand movement task (Study #1) is that the acquired data will provide a basis for valid classification in relation to performance – it can be concluded that the hypothesis has been accepted.

The discriminant analysis has identified two functions, DF_1 and DF_2, that explain 91.1 and 8.1% of the variance, respectively. The differences between the examined subsamples originate from the variables grouped in DF_1, which were statistically significant ($p \leq 0.000$). In relation to this function, the national volleyball team centroid position was shifted with -1.108 and -1.968 standard deviation values from the control group and youth volleyball team, respectively. The difference between the control and Voll_Youth groups was -0.860 standard deviation value. The factors with the greatest discriminative potential among the groups represent the temporal characteristics of the rapid hand movement, i.e., the time elapsed between the onset of the movement and the first and second tap, as defined by the variables, respectively. The established findings support hypothesis H1. The full findings supporting this study are shown in Section 7.3.

H2 - The hypothesis in relation to the measurement of shooting kinematics (Study #2) is that both accuracy and precision will be highly influenced by weapon kinematics as measured by a kinematic sensor – it can be concluded that the hypothesis has been accepted.

Moderate ($r > 0.388$, $p < 0.05$) correlations were found between the handgrip strength and shooting performance. In the interval 1.0–0.1 s before the shot moderate correlations of weapon acceleration, accuracy, and precision were determined ($r > 0.310$, $p < 0.05$) at the 6 m distance. Moderate correlations of shooting precision and rotational speed were found for the shooting distance 15 m for the same time interval ($r > 0.413$, $p < 0.05$). Moderate to high correlations of shooting accuracy, precision, and weapon kinematics were found for both shooting distances ($r > 0.405$, $p < 0.05$) in the time interval 0.1–0.0 s. Correlations of shooting performance and rotational speed indicate a high influence of the rotational component of weapon movement on the result. The established findings support hypothesis H2. The full findings supporting this study are shown in Section 8.3.

H3 – The hypothesis in relation to the karate reverse punch movement synchronization (Study #3) is that differences exist in the order of the detected events between the punches classified into different groups according to the achieved maximal velocity of the hand – it can be concluded that the hypothesis has been accepted.

A Kruskal-Wallis test revealed significant general differences in the order of occurrence of hand acceleration start ($x^2 = 10.31$, $p = 0.006$), maximal hand velocity ($x^2 = 8.64$, $p = 0.013$), maximal body velocity ($x^2 = 7.66$, $p = 0.022$), maximal hand acceleration ($x^2 = 10.37$, $p = 0.006$), maximal body acceleration ($x^2 = 7.25$, $p = 0.027$) and vertical movement onset ($x^2 = 0.45$, $p = 0.009$) between the groups in relation to the maximal velocity of the hand. This work has determined the differences in the temporal structure of the reverse punch in relation to the achieved maximal velocity of the hand as a performance indicator. The established findings support hypothesis H3. The full findings supporting this study are shown in Section 9.3.

H4 - The hypothesis in relation to the vertical jump height estimation using a kinematic sensor device placed on the metatarsal part of the foot (Study #4) is that such sensor setup will provide valid and reliable results in relation to vertical height calculation in counter-movement and squat jump tasks when compared to the force plate as a criterion device – it can be concluded that the hypothesis has been accepted.

The presented results support a high level of concurrent validity of an inertial measurement unit in relation to a force plate for estimating vertical jump height (CMJ $t = 0.897$, $p = 379$; ICC = 0.975; SQJ $t = -0.564$, $p = 0.578$; ICC = 0.921) as well as a high level of reliability (ICC > 0.872) for inertial measurement unit results. The proposed inertial measurement unit positioning may provide an accurate vertical jump height estimate for in-field measurement of jump height as an alternative to other devices. The established findings support hypothesis H4. The full findings supporting this study are shown in Section 10.3.

Hg – Valid and reliable quantification of the kinematic characteristics of human motion can be performed using MEMS kinematic sensors – based on the confirmed individual supporting hypotheses it can be concluded that the general hypothesis has been accepted.

Overall, this work has shown the applicability of kinematic sensors in the measurement of movement kinematics in different sports tasks, which adds to the existing body of knowledge in this area. In addition, this work has shown that a conceptual simplification of the task and appropriate signal and/or parameter analysis can provide excellent results for augmenting the amount of available feedback information that can be used for improvements in training.

12. References

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13. Appendices

13.1. Ethic committee approval

РЕПУБЛИКА СРБИЈА
УНИВЕРЗИТЕТ У БЕОГРАДУ
ФАКУЛТЕТ СПОРТА И ФИЗИЧКОГ ВАСПИТАЊА
02 Бр 484-2
07.3. 2011 год.
БЕОГРАД, Благоја Паровића 156

CERTIFIED TRANSLATION FROM SERBIAN INTO ENGLISH

GORDANA VEKARIĆ
PREVODILAC ZA ENGLESKI I ITALIJANSKI JEZIK
Beograd

Stamp: Republic of Serbia, University of Belgrade
Faculty of Sport and Physical Education
02 no. 484-2
24 February 2011
Belgrade, Blagoja Parovica 156

UNIVERSITY OF BELGRADE
FACULTY OF SPORT AND PHYSICAL EDUCATION

APPROVAL OF THE ETHICS COMMITTEE OF THE FACULTY OF SPORT AND PHYSICAL EDUCATION, UNIVERSITY OF BELGRADE FOR EXECUTION OF THE PROJECT "EFFECTS OF THE APPLIED PHYSICAL ACTIVITY ON LOCOMOTOR, METABOLIC, PSYCHO-SOCIAL AND EDUCATIONAL STATUS OF THE POPULATION OF THE REPUBLIC OF SERBIA" (No. 47015)

Based on the inspection of the plan of the project "Effects of the Applied Physical Activity to Locomotor, Metabolic, Psycho-Social and Educational Status of the Population of the Republic of Serbia" (No. 47015, project leader assistant prof. Milivoj Dopsaj, PhD), approved by the Ministry of Science and technological development of the Republic of Serbia within the cycle of national scientific projects for the period from 2011 to 2014, the Ethics Committee of the Faculty of Sport and Physical Education of the University of Belgrade considers that both in research conception and execution planning as well as in the application of the obtained results, from its beginning the project has been undertaken based on the principles which comply with ethical standards, ensuring thus protection for human subjects from possible violation of their psycho-social and physical benefit.

In conformity with the aforesaid opinion, the Ethics Committee of the Faculty of Sport and Physical Education of the University of Belgrade has granted the approval for realization of the research planned by the project "Effects of the Applied Physical Activity to Locomotor, Metabolic, Psycho-Social and Educational Status of the Population of the Republic of Serbia" (No. 47015, project leader Assistant prof. Milivoj Dopsaj, PhD) which is approved by the Ministry of Science and technological development of the Republic of Serbia within the cycle of national scientific projects for the period from 2011 to 2014.

For the Ethics Committee
full prof. Dušan Ugarković, signed
associate prof. Vladimir Koprivica, signed
(Stamp)

END OF TRANSLATION

№ 178/11

I CERTIFY THAT this document which has been given to me in Serbian language, has been correctly translated into English.

IN WITNESS WHEREOF I have hereunto set my hand and seal, this 1st day of March 2011 in Beograd.

My appointment is permanent.

SUDSKI PREVODILAC ZA ENGLESKI I ITALIJANSKI JEZIK GORDANA VEKARIĆ Beograd

Gordana Vekarić, Sworn to Court
Interpreter for English and Italian language

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Appointed by the Decision of the Republic Minister of Justice,
Belgrade, Serbia № 74-02-46/91-03

13.2. Published paper I

Hindawi
Applied Bionics and Biomechanics
Volume 2020, Article ID 7919514, 7 pages
https://doi.org/10.1155/2020/7919514

Research Article

Potential of IMU-Based Systems in Measuring Single Rapid Movement Variables in Females with Different Training Backgrounds and Specialization

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Received 26 December 2019; Revised 20 March 2020; Accepted 17 June 2020; Published 1 July 2020

Academic Editor: Juri Taborri

The aim of this paper is to determine the discriminative potential of the IMU-based system for the measurement of rapid hand movement properties, i.e., relevant kinematic variables in relation to different groups of participants. The measurement of the kinematics of the rapid hand movement was performed using a standard hand tapping test. The sample in this research included a total of 70 female participants and was divided into 3 subsamples. The discriminant analysis has identified two functions, DF_1 and DF_2, that explain 91.1 and 8.1% of the variance, respectively. The differences between the examined subsamples originate from the variables grouped in DF_1, which were statistically significant ($p \leq 0.000$). In relation to this function, the national volleyball team centroid position was shifted with -1.108 and -1.968 standard deviation values from the control group and youth volleyball team, respectively. The difference between control and Voll_Youth groups was -0.860 standard deviation value. The factors with the greatest discriminative potential among the groups represent the temporal characteristics of the rapid hand movement, i.e., the time elapsed between the onset of the movement and the first and second tap, as defined by the variables t_1 and t_2, respectively. The established findings clearly indicate that IMU sensors are practically applicable in relation to the sensitive measurement of rapid arm movement capability of female athletes.

13.3. Published paper II

INTERNATIONAL JOURNAL OF PERFORMANCE ANALYSIS IN SPORT
2020, VOL. 20, NO. 6, 1107–1119
https://doi.org/10.1080/24748668.2020.1833624

Routledge
Taylor & Francis Group

Check for updates

The relationship of pistol movement measured by a kinematic sensor, shooting performance and handgrip strength

Stefan Marković [a], Milivoj Dopsaj [a,b], Anton Umek [c], Goran Prebeg [a] and Anton Kos [c]

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ABSTRACT

This paper aims to determine the relationship between the measures of shooting performance handgrip strength and weapon kinematics during different phases of the shot. The research included 35 participants who performed shooting sessions on 6 and 15 m shooting distance. Moderate ($r > 0.388$, $p < 0.05$) correlations were found between the handgrip strength and shooting performance. In the interval 1.0–0.1 s before the shot moderate correlations of weapon acceleration, accuracy and precision were determined ($r > 0.310$, $p < 0.05$) at the 6 m distance. Moderate correlations of shooting precision and rotational speed were found for the shooting distance 15 m for the same time interval ($r > 0.413$, $p < 0.05$). Moderate to high correlations of shooting accuracy, precision and weapon kinematics were found for both shooting distances ($r > 0.405$, $p < 0.05$) in the time interval 0.1–0.0 s. Absolute handgrip strength was a superior predictor of shooting performance than relative strength. Precision was more related to handgrip strength than accuracy and this relationship was more pronounced with distance. Correlations of shooting performance and rotational speed indicate high influence of the rotational component of weapon movement on the result.

ARTICLE HISTORY
Received 14 May 2020
Accepted 5 October 2020

KEYWORDS
Kinematic sensor; pistol shooting; weapon movement; accuracy; precision; handgrip strength

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13.4. Published paper III

sensors

MDPI

Article

Use of IMU in Differential Analysis of the Reverse Punch Temporal Structure in Relation to the Achieved Maximal Hand Velocity

Stefan Marković [1,2,*], Anton Kos [1], Vesna Vuković [2], Milivoj Dopsaj [2,3], Nenad Koropanovski [4] and Anton Umek [1]

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check for updates

Citation: Marković, S.; Kos, A.; Vuković, V.; Dopsaj, M.; Koropanovski, N.; Umek, A. Use of IMU in Differential Analysis of the Reverse Punch Temporal Structure in Relation to the Achieved Maximal Hand Velocity. *Sensors* **2021**, *21*, 4148. https://doi.org/10.3390/s21124148

Academic Editors: Hristijan Gjoreski, Mitja Luštrek and Angelo Maria Sabatini

Received: 28 March 2021
Accepted: 8 June 2021
Published: 17 June 2021

Abstract: To achieve good performance, athletes need to synchronize a series of movements in an optimal manner. One of the indicators used to monitor this is the order of occurrence of relevant events in the movement timeline. However, monitoring of this characteristic of rapid movement is practically limited to the laboratory settings, in which motion tracking systems can be used to acquire relevant data. Our motivation is to implement a simple-to-use and robust IMU-based solution suitable for everyday praxis. In this way, repetitive execution of technique can be constantly monitored. This provides augmented feedback to coaches and athletes and is relevant in the context of prevention of stabilization of errors, as well as monitoring for the effects of fatigue. In this research, acceleration and rotational speed signal acquired from a pair of IMUs (Inertial Measurement Unit) is used for detection of the time of occurrence of events. The research included 165 individual strikes performed by 14 elite and national-level karate competitors. All strikes were classified as slow, average, or fast based on the achieved maximal velocity of the hand. A Kruskal–Wallis test revealed significant general differences in the order of occurrence of hand acceleration start, maximal hand velocity, maximal body velocity, maximal hand acceleration, maximal body acceleration, and vertical movement onset between the groups. Partial differences were determined using a Mann–Whitney test. This paper determines the differences in the temporal structure of the reverse punch in relation to the achieved maximal velocity of the hand as a performance indicator. Detecting the time of occurrence of events using IMUs is a new method for measuring motion synchronization that provides a new insight into the coordination of articulated human movements. Such application of IMU can provide additional information about the studied structure of rapid discrete movements in various sporting activities that are otherwise imperceptible to human senses.

Keywords: IMU; karate; punch velocity; gyaku zuki; event timeline; accelerometer; gyroscope; sensor fusion

13.5. Published paper IV

applied sciences

MDPI

Article

Can IMU Provide an Accurate Vertical Jump Height Estimate?

Stefan Marković [1,2,*], Milivoj Dopsaj [2,3], Sašo Tomažič [1], Anton Kos [1], Aleksandar Nedeljković [2] and Anton Umek [1]

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Abstract: The aim of the present study was to determine if an inertial measurement unit placed on the metatarsal part of the foot can provide valid and reliable data for an accurate estimate of vertical jump height. Thirteen female volleyball players participated in the study. All players were members of the Republic of Serbia national team. Measurement of the vertical jump height was performed for the two exemplary jumping tasks, squat jump and counter-movement jump. Vertical jump height estimation was performed using the flight time method for both devices. The presented results support a high level of concurrent validity of an inertial measurement unit in relation to a force plate for estimating vertical jump height (CMJ $t = 0.897$, $p = 379$; ICC = 0.975; SQJ $t = -0.564$, $p = 0.578$; ICC = 0.921) as well as a high level of reliability (ICC > 0.872) for inertial measurement unit results. The proposed inertial measurement unit positioning may provide an accurate vertical jump height estimate for in-field measurement of jump height as an alternative to other devices. The principal advantages include the small size of the sensor unit and possible simultaneous monitoring of multiple athletes.

Keywords: IMU; force plate; squat jump; counter-movement jump; vertical jump

Citation: Marković, S.; Dopsaj, M.; Tomažič, S.; Kos, A.; Nedeljković, A.; Umek, A. Can IMU Provide an Accurate Vertical Jump Height Estimate?. *Appl. Sci.* **2021**, *11*, 12025. https://doi.org/10.3390/app112412025

Academic Editors: Mark King and Jesús García Pallarés

Received: 1 October 2021
Accepted: 10 December 2021
Published: 17 December 2021

13.6. Biography

Stefan Marković was born on June 25th 1985. He completed Bachelor studies on the University of Belgrade, Faculty of sport and physical education with an average grade of 8.98 in 2016. He completed Master studies on the University of Belgrade, Faculty of sport and physical education with an average grade of 9.89 in 2017. He enrolled in the Doctoral academic studies at the University of Belgrade, Faculty of sport and physical education in 2017. During the school year 2019/20 he took part in the Erasmus+ student exchange program at the University of Ljubljana, Faculty of Electrical Engineering. He speaks English language.

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