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Wearable Sensors for Sport Biomechanics Applications

Lead Guest Editor: Juri Taborri
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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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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.

1. Introduction

In recent years, there has been a rapid development of microelectromechanical sensor systems (MEMS). Along with it came the implementation and application of such systems in different professional environments as well as in everyday use [1]. In this context, the system of sport is not an exception, and various wearable sensors have been developed and used in testing, training, and competition in order to provide new, or more in-depth, information regarding different aspects of sports performance. In essence, this reflects more broad tendencies regarding the implementation of new technologies for the purposes of obtaining more sensitive and sport-specific information in relation to the level of achieved preparedness in elite athletes [2].

Miniature inertial measurement unit (IMU) is a typical example of the MEMS technology which has been increasingly used as a means for motion analysis [3] for the purposes of sports science and praxis. Typically, an IMU that incorporates a triaxial accelerometer, gyroscope, and magnetometer is built into a miniature wearable device [4]. This allows measurement of acceleration, angular velocity, and orientation and also permits sensor fusion for tracking of three-dimensional movements to a variable extent of precision. In addition, it is possible to use an IMU in order to obtain relevant information about the temporal characteristics of the analyzed movements [5]. In this case, the sampling frequency of the system determines the level of measurement precision. Primary applications of IMU-based systems in sports training, testing, and competition are related to either concurrent or terminal biomechanical biofeedback [1] or to the assessment of the physical characteristics relevant for performance and injury prevention [6–8].

The development of sports science increasingly requires a multistructured, integrative approach to information gathering in both laboratory and field testing conditions. This requires the application of multiple measurement methods and technologies [9] in order to obtain relevant information regarding the level of achieved physical fitness during different phases of athletes' preparation. In addition to being a basis for assessment, these results can be used for the purposes of calculating the potential of physical abilities and the efficiency of athletes' performance [10, 11]. In this sense, sports science and praxis employ both basic, i.e., universal, and specific testing batteries [12] for permanent and periodical monitoring of physical properties, expressed in nonspecific conditions as well as in specific conditions of competitive stress [13]. 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 movements in basically all sports [14]. Accordingly, regardless of the specificity of the testing conditions, it is necessary to provide relevant information about the athletes' potential in this aspect. In this context, volleyball is a typical example of a sport that sets high and complex technical, tactical, and physical requirements for the players. This, in turn, requires overall development of motor abilities and specific motor skills [15] which can be considered a multidimensional, multistage task that requires constant monitoring.

As previously mentioned, IMU-based measurement systems have been increasingly used in different sport settings for various purposes including performance and technique evaluation [16], although their application in measurement of fast hand and arm movements has been fairly limited. In this context, baseball pitching has been the most frequently researched topic due to the high incidence of injuries related to this particular type of throwing motion and the need to accurately measure the dynamics of the involved segments during peak activity in order to quantify relevant aspects of performance [17]. As throwing a baseball and hitting a volleyball are similar in overhead functional demand, although they generate different kinematic patterns [18], IMU-based systems are also applicable in this context and were used in recent studies for classification of volleyball players based on spiking performance and evaluation of wrist speed and as a part of measurement systems used for movement classification [19–21].

In volleyball, high arm speed is a general prerequisite of successful performance, as it is generally required for efficient spiking [22]. Therefore, relevant information regarding the differences between groups in relation to the kinematic characteristics of rapid arm and hand movement can contribute to the better understanding of the stages of athletes' development and potential effects of training and selection process on their capabilities in this regard. Comparison of volleyball players of different age categories but similar competitive ranking within each category and physically active controls (with no volleyball background) can provide insight into some of the attributes that are unique to the players [23] or can serve as a basis for identification of the individuals that are potentially more capable in this regard. In relation to the aforementioned, the hand tapping test was chosen for the purposes of this research as it is not sport-specific and it is widely used as a part of basic test batteries in different sports as well as in testing of basic motor abilities in a nonathlete population.

The aim of this paper is to determine the discriminative potential of the IMU-based system for measurement of rapid hand movement properties, i.e., to define relevant kinematic variables in relation to different groups of participants.

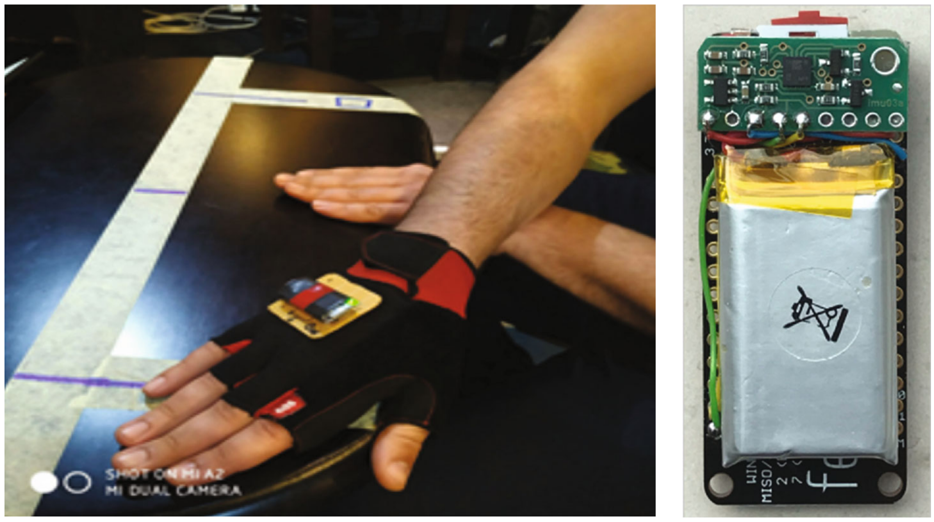
2. Materials and Methods

2.1. The Research Sample. The sample in this research included a total of 70 female participants. The overall sample was divided into 3 groups, of which one included physically active controls (age = 22.3 ± 1.9 years, BH = 168.8 ± 5.3 cm, BW = 64.5 ± 2.8 kg), while the other two consisted of the members of the Republic of Serbia national volleyball team (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.

2.2. Measurement Methods. The measurement of the kinematics of the rapid hand movement was performed using a test that represents the gold standard in the measurement of rapid movements of the extremities—standard hand tapping test [9, 24, 25]. This standard test included lateral alternating hand movement between two markers positioned at the 50 cm distance on the table in front of the participant. The test was performed in an upright sitting position with the dominant hand, which was initially placed on the mark at the opposite side, while the nondominant hand was placed at the mark positioned at the midlength of the movement distance, as shown in Figure 1(a). When ready, the subject performed a maximally fast movement. After performing 2 pretest familiarization trials, each participant performed three trials separated with at least 3 minutes of rest [11]. The best result was taken for further statistical processing [26].

For the purposes of this research, we developed a portable measurement system, which allows for quick setup. The wireless sensor device is connected to a laptop running the LabView application. A custom-made wireless sensor device includes an IMU MEMS sensor, a microcontroller with a built-in Wi-Fi communication module, and a LiPo battery for multihour operation. Figure 1(b) shows a custom-made sensor device without a protective housing. The sensor device is attached to the glove as shown in Figure 1(a). The acceleration in the Y-axis corresponds to the line of hand movement, i.e., the line connecting the markers.

The sensor device is equipped with a combined 3D accelerometer and 3D gyroscope (LSM6DS33, STMicroelectronics, Genève, Switzerland) [27]; however, for the purpose of our research, we used only accelerometer data. The sampling frequency is 200 Hz, and the dynamic range of the



(a) (b)

Figure 1: (a) The initial position of the subject's hand with the IMU sensor attached to the glove. (b) A custom-made wireless sensor device (uncovered).

accelerometer is ±16 g_0. The wireless sensor device continuously sends data via a Wi-Fi interface while a LabVIEW application is used for acceleration signal processing and kinematic variable data acquisition.

A custom LabView (LabView 2019, National Instruments, Austin, Texas) application was used in order to process the acceleration signal. The LabView application contains a module for receiving accelerometer samples in UDP packets, and the obtained accelerometer signal was filtered with a low-pass Butterworth filter (order = 5, fcof = 40 Hz). The relevant variables in the movement kinematics were automatically identified after the onset of the motion, which was detected when the absolute acceleration exceeded 1.15 g_0. The application implements automatic threshold and peak detection using predefined SubVIs provided by National Instruments for both A_Y and abs (A), thus providing the location and/or magnitude of relevant kinematic and temporal variables. Detection of the acceleration gradient variables was performed using the peak detector SubVI on the signal obtained by derivation of the acceleration over time.

2.3. Variables. The following variables acquired from the processed hand acceleration signal were used in order to define the relevant temporal and kinematic characteristics of the movement:

(i) t_1 is the time from the start of the movement to the first tap of the hand (expressed in s)

(ii) t_2 is the time from the first tap to the second tap of the hand (expressed in s)

(iii) A_1 is the maximal acceleration (expressed as a multiplier of g_0)

(iv) A_2 is the maximal deceleration (expressed as a multiplier of g_0)

(v) GA_1 is the maximal acceleration gradient (expressed in $g_0 \cdot s^{-1}$)

(vi) GA_2 is the maximal deceleration gradient (expressed in $g_0 \cdot s^{-1}$)

It should be noted that all acceleration-related variables were measured in the first part of tapping, prior to the first hand tap. The examined variables and the time frame of events are shown on a typical example of the acceleration signal (Figure 2).

2.4. Statistical Analysis. For the purposes of this paper, 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 groups' 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 $p \leq 0.05$ [28]. All data analyses were conducted using Excel 2013 and IBM SPSS v23 statistical software.

3. Results and Discussion

Table 1 shows the results of the descriptive statistical analysis of the relevant kinematic variables in relation to the examined groups, as well as the results of the one-sample nonparametric Kolmogorov-Smirnov goodness-of-fit test.

Table 2 shows the summary of the canonical discriminant functions and the results of the general statistical differences between groups in relation to the examined variables.

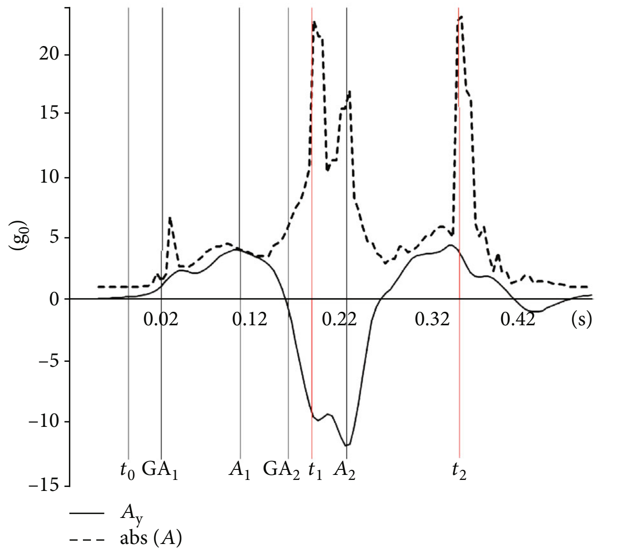


Figure 2: Absolute acceleration (abs) and acceleration in the Y-(dominant) axis with the time frame of relevant events.

Table 3 shows the structure matrix of the extracted functions explaining the determined general differences between groups.

Table 4 shows the classification of the group membership in relation to the results of the discriminant analysis based on the relevant kinematic variables of rapid hand movement.

Figure 3 shows 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.

Based on the results of the descriptive statistical analysis, it was determined that the obtained results of the examined kinematic variables of rapid hand movement have acceptable variation, given the fact that the coefficient of variation is in the range from 7.87 to 45.00 for t_2 in Voll_Youth and GA_2 in control samples, respectively. The results of the Kolmogorov-Smirnov goodness-of-fit test indicate that the examined variables are normally distributed on a general level (Table 1). The results of Box's test of equality of covariance matrices have shown that the multiple distribution of the examined groups is 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 have average homogeneity [29] and normal distribution and belong to the same measurement area which makes them representative in terms of further scientific interpretation.

The discriminant analysis has identified two functions, DF_1 and DF_2, that explain 91.9 and 8.1% of the variance, respectively. It was determined that DF_1 is statistically significant ($p \leq 0.000$). This function is composed of the variables t_1 and t_2. The second function DF_2 is composed of the variables A_1, A_2, GA_1, and GA_2. DF_2 reached a p value of 0.616, thus yielding nonsignificant results (Table 2). This indicates that the differences between the examined subsamples originate from the variables grouped in DF_1, i.e., the first function. The centroid positions of the examined groups control, Voll_Nat_Team, and Voll_Youth in relation to the function DF_1 are -0.112, -1.220, and 0.748, respectively (Figure 3). These results show that, in relation to DF_1, the Voll_Nat_Team group centroid position is shifted with -1.968 and -1.108 standard deviation values from the Voll_Youth and the control group, respectively. The difference between control and Voll_Youth is -0.860. The second discriminant function (DF_2) did not show a significant difference between the observed groups; thus, the centroid positions of the groups in relation to this function are similar (Figure 3). The factors with the greatest discriminative value 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 (t_1) and second (t_2) tap, as shown in Table 3.

Regarding the efficiency of the IMU-based measurement system in relation to the discrimination of the examined subsamples from the aspect of kinematic characteristics relevant for the rapid hand movement, it was determined that it was 65.7% overall (Table 4). It should be pointed out that the highest accuracy of classification (80.6%) was determined in the subsample of young volleyball players (Voll_Youth), while players in the control group were classified as having the lowest accuracy (40.9%). Based on the kinematic characteristics of rapid hand movement, 36.4 and 22.7% of the control group was classified in the subsamples Voll_Youth and Voll_Nat_Team, respectively (Table 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 presented results show the potential of IMU sensors in relation to the measurement of rapid movement kinematics. The discriminative nature of the obtained results indicates the applicability of such systems for the purposes of assessment, monitoring, and even selection of athletes.

4. Conclusions

The aim of this paper was to determine the discriminative potential of IMU sensor technology in detecting single rapid movement variables/characteristics in females with different training backgrounds and specialization. Rapid hand movement properties, i.e., relevant kinematic variables in relation to different groups of participants, were examined. The measurement of the kinematic variables 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, 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. The discriminant analysis has identified two functions, DF_1 and DF_2, that explain 91.9 and 8.1% of the variance, respectively. The differences between the examined subsamples originate from the variables grouped in extracted function DF_1, which was statistically significant at the level $p \leq 0.000$. In relation to

Table 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	SEM	StDev	cV%	Min	Max	K-S Z	Sig.
Control									
t_1 (s)	22	0.23	0.01	0.03	14.20	0.19	0.29	0.611	0.849
t_2 (s)	22	0.43	0.01	0.05	12.50	0.34	0.54	0.741	0.642
A_1 (g_0)	22	3.87	0.25	1.17	30.23	2.02	6.23	0.351	1.000
A_2 (g_0)	22	8.33	0.44	2.06	24.75	5.34	12.24	0.713	0.689
GA_1 ($g_0 \cdot s^{-1}$)	22	70.94	5.21	24.42	34.42	36.00	122.13	0.834	0.491
GA_2 ($g_0 \cdot s^{-1}$)	22	211.73	20.31	95.27	45.00	84.34	485.88	0.961	0.314
Voll_Nat_Team									
	N	Mean	SEM	StDev	cV%	Min	Max	K-S Z	Sig.
t_1 (s)	17	0.21	0.01	0.03	13.92	0.17	0.26	0.590	0.877
t_2 (s)	17	0.40	0.01	0.04	9.63	0.37	0.50	1.190	0.117
A_1 (g_0)	17	3.88	0.21	0.88	22.63	2.17	5.32	0.563	0.909
A_2 (g_0)	17	8.35	0.46	1.91	22.88	4.39	12.07	0.440	0.990
GA_1 ($g_0 \cdot s^{-1}$)	17	57.30	5.81	23.97	41.84	23.59	109.81	0.433	0.992
GA_2 ($g_0 \cdot s^{-1}$)	17	229.26	17.62	72.63	31.68	142.95	394.64	0.775	0.586
Voll_Youth									
	N	Mean	SEM	StDev	cV%	Min	Max	K-S Z	Sig.
t_1 (s)	31	0.24	0.00	0.03	11.52	0.18	0.30	0.679	0.746
t_2 (s)	31	0.45	0.01	0.04	7.87	0.40	0.52	0.815	0.520
A_1 (g_0)	31	3.78	0.18	0.99	26.25	2.48	5.89	0.684	0.737
A_2 (g_0)	31	8.94	0.43	2.42	27.04	4.90	14.16	0.725	0.669
GA_1 ($g_0 \cdot s^{-1}$)	31	72.34	4.63	25.79	35.65	37.88	154.98	0.908	0.382
GA_2 ($g_0 \cdot s^{-1}$)	31	252.19	17.87	99.51	39.46	96.47	520.85	0.754	0.620

Table 2: The summary of canonical discriminant functions and general intergroup 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

Table 3: The structure matrix.

	Function	
	DF_1	DF_2
t_1	0.516	-0.007
t_2	0.408	-0.209
A_1	0.145	0.654
A_2	0.295	-0.412
GA_1	0.144	0.318
GA_2	-0.056	-0.093

Table 4: Classification results.

		Groups	Predicted group membership: Control	Voll_ Nat_ Team	Voll_ Youth	Total
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

65.7% of the original grouped cases were correctly classified.

this function, the Voll_Nat_Team group centroid position was shifted with -1.108 standard deviation values from the control and -1.968 standard deviation values from the Voll_ Youth group. 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 are the variables of the temporal characteristics of

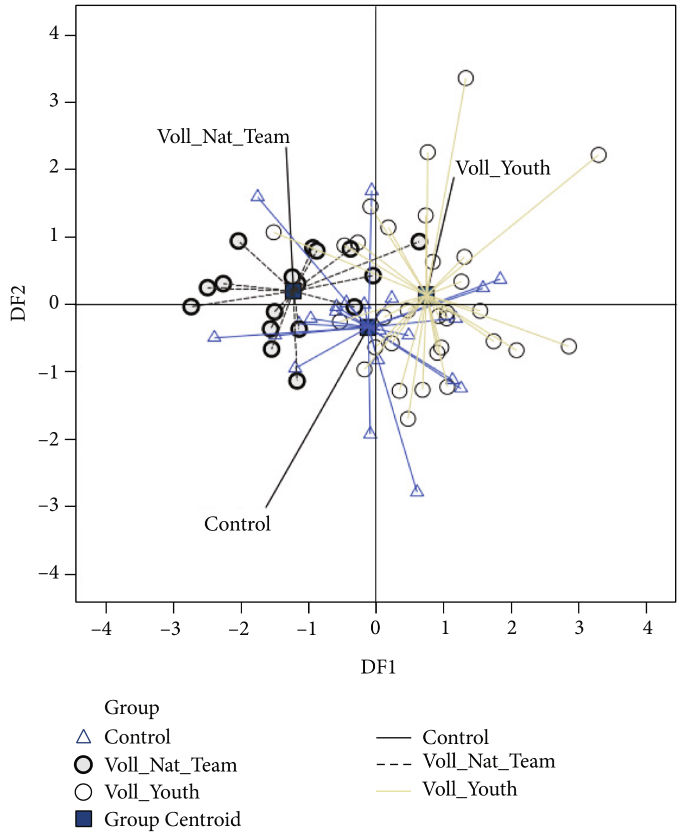


Figure 3: The graphical representation of the centroid position of the examined subsamples.

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. The established findings clearly indicate that IMU sensors are practically applicable in this context and can be included as a new technology used for the purposes of assessment, monitoring, and selection of athletes.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

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Conflicts of Interest

The authors of the paper declare no conflict of interest.

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Review Article

Sport Biomechanics Applications Using Inertial, Force, and EMG Sensors: A Literature Overview

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In the last few decades, a number of technological developments have advanced the spread of wearable sensors for the assessment of human motion. These sensors have been also developed to assess athletes' performance, providing useful guidelines for coaching, as well as for injury prevention. The data from these sensors provides key performance outcomes as well as more detailed kinematic, kinetic, and electromyographic data that provides insight into how the performance was obtained. From this perspective, inertial sensors, force sensors, and electromyography appear to be the most appropriate wearable sensors to use. Several studies were conducted to verify the feasibility of using wearable sensors for sport applications by using both commercially available and customized sensors. The present study seeks to provide an overview of sport biomechanics applications found from recent literature using wearable sensors, highlighting some information related to the used sensors and analysis methods. From the literature review results, it appears that inertial sensors are the most widespread sensors for assessing athletes' performance; however, there still exist applications for force sensors and electromyography in this context. The main sport assessed in the studies was running, even though the range of sports examined was quite high. The provided overview can be useful for researchers, athletes, and coaches to understand the technologies currently available for sport performance assessment.

1. Introduction

Recent statistics showed that about 50% of the European population performs a sport activity at least once a week starting from 15 years old [1]. It is well known that sports, or physical activities more generally, have a positive impact on quality of life. Several studies demonstrated the benefits in terms of life satisfaction, health, well-being, and educational and social participation [2, 3]. In addition, perhaps due to the growing number of people who compete in a wide variety of sports and recreational levels, the elite level requirements are constantly increasing. Recent technological developments have contributed to these increasing competitive levels, with these devices used to monitor sport training and competition performance, especially from a sport biomechanics perspective. Sport biomechanics represents the science that provides quantitative (and sometimes qualitative) assessments of sport performance; in particular, the kinematics and kinetics of sport movements [4]. Measuring and characterizing human movements during sporting activities are nowadays a crucial aspect for coaching programs in order to assess athletes' performance, to improve technique, and to prevent injuries [5–7]. In the past, 3D video analysis through optoelectronic systems represented the most widespread approach to analyse athlete behaviour during training or competition. Unfortunately, the 3D optoelectronic-based methodologies still have several limitations for widespread use in sport, such as difficulties in analysing human movement in outdoor environments, the time spent and the skills needed for the subjects' sensorization and the limited calibration volume in which the analyses can be performed [8]. The intrinsic limitations of using reflective markers, i.e. indoor analysis and competences required for the sensorization, have been overcome by markerless systems or specific processing systems, such as OpenSim or the use of artificial intelligence algorithms—for example, the concurrent neural network [9, 10]. Nowadays, sport biomechanics is, generally, performed by using wearable sensors that allow ensuring noninvasive data acquisition during the execution of movements [11]. Furthermore, wearable sensors allow the sporting activity to be performed in the natural environment, overcoming the environment limitation of laboratory testing, such as the use of the optoelectronic 3D system that is still considered the gold standard for movement analysis [11, 12]. Among others, inertial sensors [7, 13–49] force sensors [43, 50–70], and electromyography probes [71–137] are widely used for objectively and unobtrusively quantifying kinematics, kinetics, and muscle activity during sporting activities. One promising direction in wearable sensor use is real-time biofeedback systems [138] that can offer concurrent augmented feedback information to athletes and/or coaches [7, 139–142].

Although several systematic reviews already available in literature demonstrated the reliability, validity, and utility of inertial sensors for sport applications [8, 143, 144], an overview on specific applications that can be implemented by analysing kinematics, kinetics, muscle activity, and physiological parameters through wearable sensors is missing. From this perspective, we aimed to provide an overview on applications of sport biomechanics that require the use of wearable sensors, not only the inertial ones.

2. Materials and Methods

2.1. Search Strategy. Scopus, Web of Science, and PubMed databases were used to perform the literature review. Only studies that used wearable sensors for sport applications were considered; in particular, three categories were selected before the literature review: inertial sensors, force sensors, and electromyographic units. The start and the end of the literature review were July 2019 and November 2019, respectively. The following base keywords were used for the search: *sports*, *wearable sensors*, *wearable devices*, *biomechanics*, and *wireless.* More specifically, as regards inertial sensors, the following keywords were added: *IMU*, *inertial sensors*, *motion sensors*, and *wearable IMU*. Concerning the force measurements, *force* and *pressure* were used as additional keywords. As regards electromyography applications, these further keywords were used: *EMG*, *motor module*, *muscle coordination*, *muscle synergies*, *muscles*, *electromyography*, *patterned control*, *activation patterns*, *locomotor primitives*, and *modular organization*. In order to avoid bias in the search due to variations of root words, we also considered wildcard symbols, such as hyphens or inverted commas. The bibliography of the found studies was further checked in order to include relevant works accidentally omitted from the keyword-based research [11].

2.2. Inclusion Criteria. Studies were initially selected based on the relevance of the title and abstract. Thus, studies had to meet the following inclusion criteria: (i) only studies written in English were considered for the successive analysis, (ii) only studies published from 2010 onwards were included in order to avoid adding in the review outdated technologies, and (iii) conference proceedings were deleted if the same authors published also a journal paper regarding the same topic.

2.3. Data Extraction. Only studies that passed all the previous inclusion criteria were downloaded and managed through the Mendeley Desktop system. Since the review aimed at providing an overview of several wearable sensors used for sports, the studies were firstly categorized based on the type of wearable sensors used. The following information were gathered from each paper: (i) the aims, (ii) the examined sports, (iii) the kind of participants (e.g., inexperienced, recreational, and elite), (iv) the experimental setup, (v) how data was processed and analysed, and (vi) the results and conclusions. Studies that did not involve human subjects were automatically excluded.

2.4. Quality Assessment. The quality of each study was assessed in terms of internal, statistical, and external validity using the reported questionnaire [145]. All the authors were asked to answer an 18-item checklist, which is an optimization of similar ones used for reviews [146–150]. In particular, the checklist (Table 1) allowed us to assess information on internal (question numbers 1, 3, 4, 6, 7, 9, 12, 13, and 14), statistical (question numbers 15, 16, 17, and 18), and external (question numbers 2, 3, 5, 6, 8, 10, and 11) validity. The authors assigned a positive (one point) or negative (zero points) to each questionnaire item, and the final score was calculated by summing the assigned points. A study was considered as "high-quality" if it reached a score equal or greater than 11 (~61% of the maximum) in the evaluation of the majority of authors [147, 149]. Among the articles identified as "high-quality," the authors selected a subset of papers that would be more fully examined in Results and Discussions. This selection was performed by considering only the studies that achieved a quality score of at least 15, in order to include studies in which the risk of bias was low.

For the sake of clarity, A.K. and A.U. performed the review of the inertial sensors, C.U. and E.K. took care of the force sensors, A.S. and J.T. performed the review of the EMG sensors, and J.T., J.K., and S.R. supervised the data quality assessment in order to avoid bias.

Table 1: Criteria for quality assessment of the internal validity (IV), statistical validity (SV), and external validity (EV).

Criteria		Assessment property
Aim of the work		
(1)	Description of a specific, clearly stated purpose	IV
(2)	The research question is scientifically relevant	EV
Inclusion criteria (selection bias)		
(3)	Description of inclusion and exclusion criteria	IV-EV
(4)	Inclusion and exclusion criteria are the same for all tested groups	IV
(5)	Inclusion and exclusion criteria reflect the general population	EV
Data collection (performance bias)		
(6)	Data collection is clearly described and reliable	IV-EV
(7)	Same data collection method used for all the athletes	IV
(8)	The used setup is wearable	EV
Data loss (attrition bias)		
(9)	Different data loss between groups	IV
(10)	Data loss < 20%	EV
Outcome (detection bias)		
(11)	Outcomes allow tangible application	EV
(12)	Outcomes are the same for all the athletes	IV
Data presentation		
(13)	Frequencies of most important outcome measures	IV
(14)	Presentation of the data is sufficient to assess the adequacy of the analysis	IV
Statistical approach		
(15)	Appropriate statistical analysis techniques	SV
(16)	Clearly state the statistical test used	SV
(17)	State and reference the analytical software used	SV
(18)	At least 10 subjects	SV

3. Results and Discussions

3.1. Inertial Sensors. The use of inertial sensors and wearable sensor devices in sports has boomed over the last decade. This is demonstrated by a simple search on Scopus using the keywords “sports” and “inertial sensors” that identified a total of 37 articles published in January to May 2020, a value that is identical to the number of articles found using the same search terms over the period 2004-2009. Modern inertial sensors are miniature low-power chips integrated into wearable sensor devices or smart equipment. Today’s inertial sensors predominantly fall into the group of microelectromechanical systems (MEMS) that are portable, miniature, lightweight, inexpensive, and low power and generally include any combination of accelerometer, gyroscope, and magnetometer.

Inertial sensors are used for the measurement of static and dynamic states of the athlete’s body. In the static state, some of the most important parameters are spatial position, orientation, posture, angles between body parts, etc. In the dynamic state, additional important parameters may include displacement, trajectory, velocity, linear acceleration, jerk (change of acceleration), angular velocity, angular acceleration, etc. While linear acceleration (accelerometer), angular velocity (gyroscope), and orientation (magnetometer) can all be measured directly, all other kinematic parameters must be derived from one or more measured quantities. For example, the velocity of a body is calculated by integrating its acceleration over time and its rotation angle is calculated by integrating its angular velocity over time. The measured and the derived results can be affected by inaccuracies of MEMS sensors. The discussion of this topic is not in the scope of this paper, but some useful guidelines on the proper use of MEMS inertial sensors can be found in [151–153].

The number of papers dealing with the use of inertial sensors in sport is far too great to process; a simple search in the SCOPUS database alone yielded over 1700 such papers. We have narrowed it down, as described in the search strategy in Section 2. The initial search, using the defined search terms, yielded 162 papers. After the author, duplicate, and language checks, 154 papers remained. After removing the older conference papers and conference papers that were later published in a journal, we have read the abstract of the remaining 113 papers. We have then excluded all review papers and articles concerning inertial, force, and EMG sensors, human activity detection, and detection of human states. From the remaining 64 papers, we excluded all general and non-sport-specific papers, which left 42 papers for thorough reading and analysis. The selection process is shown in Figure 1.

After analysing the chosen papers, we describe the use of inertial sensors based on the sport activity. More specifically, Table 2 shows the distribution of the included studies based on the specific sport.

Wearable sensor devices with integrated inertial sensors can be used for measuring and evaluating practically any activity in sport. Due to a large number of possible activities, we discuss the use of inertial sensors on a few groups of examples related to different sports.

Very frequent use of inertial sensors for various purposes was found in *walking and running actions*. The cyclic nature of such movements allows the use of a wide number of analysis techniques for the extraction of kinematic parameters or other results of interest. Analysing walking was perhaps the least difficult task within this group of actions, and there were numerous studies in this area. Flores-Morales et al. [21] used a mobile sensor device with six inertial sensors attached to the lower extremities of subjects and analysed the acquired data with the OpenSim system, which is open-source software, to create and analyse dynamic simulations of movement. An interesting approach, using the autocorrelation function for the assessment of regularity of cyclic human movements, including gait, was presented in [22]. A more

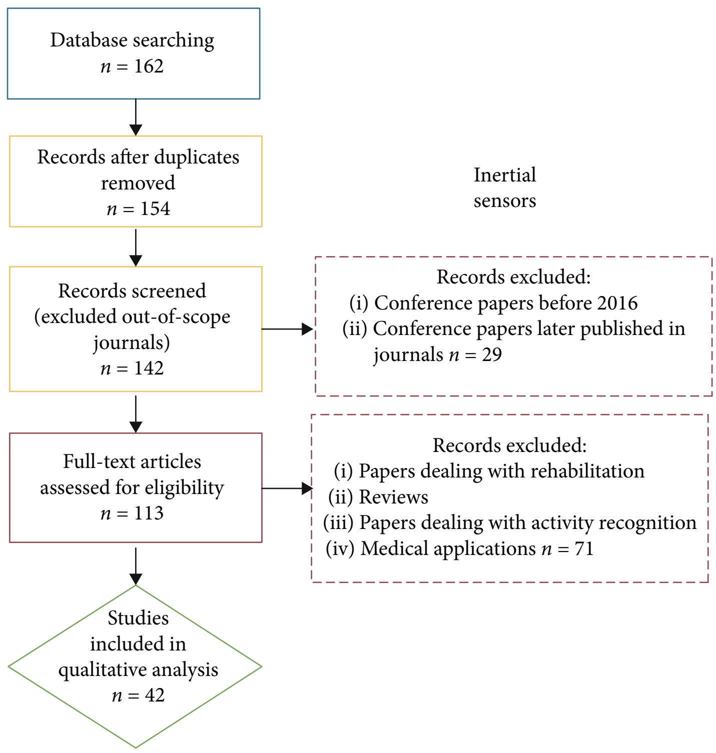

Figure 1: Selection process of papers focused on inertial sensors. Blue block represents the identification step, yellow blocks the screening step, red blocks the eligibility step, and green block the inclusion step.

Table 2: References of inertial sensor measurement based on different analysed sports.

Sport/function	Number of studies	References
Gait	2	[21, 22]
Nordic walking	1	[23]
Running	3	[24–26]
Sprint	2	[27, 28]
Badminton	1	[29]
Table tennis	1	[30]
Tennis	3	[31–33]
Baseball	2	[34, 35]
Basketball	3	[37–39]
Volleyball	1	[36]
Rugby union	2	[154, 155]
Cross-country skiing	1	[40]
Roller skiing	1	[41]
Ski jumping	1	[42]
Alpine skiing	3	[43–45]
Swimming	2	[46, 47]

energetic version of walking gait is Nordic walking. Nordic walking has been derived from snow skiing, whereby the individual uses handheld poles using a coordination pattern similar to cross-country skiing that requires substantially more upper body muscular involvement than typical walking movements. Derungs et al. [23] used 14 IMUs and regression methods for the estimation of acquired skills and detection of potential coordination mistakes in Nordic walking. The next step is using inertial sensors occurring in *running actions*. Since running is a more dynamic form of gait than walking, the requirements for sensors are higher. The determination of the foot strike pattern was the main idea in [24]. The authors used accelerometers and gyroscopes to calculate the stride length and determine the landing strategies at three running speeds. Similarly, Zrenner and colleagues [25] compared different statistical, DSP (Digital Signal Processing), and deep learning algorithms used for calculating the velocity and stride length in running using IMUs. Muniz-Pardos et al. [26] aimed to evaluate the running economy and foot mechanics in elite runners, which were determined through the use of an inertial sensor worn on the foot of the runners. The most dynamic action in this gait group is *sprint*. An accelerometer positioned on the sprinters' waist was used in [27] for the assessment of sprint based on the regression machine learning method. Mertens et al. [28] employed sophisticated validation methods including laser pistols and real-time kinematic GPS systems for the measurement of the sprint velocity using only one IMU with an integrated accelerometer and gyroscope.

Another group of activities, where inertial sensors can be extremely beneficial, are *racket and bat sports*. A typical use of IMU in such actions is on the hand/wrist/arm of the athlete or integrated into the equipment. Wang and colleagues [29] devised an Internet of Things (IoT) platform for use in racket sports. They placed an IMU on the wrist of the athlete and processed the acquired data through the machine learning methods. They performed skill assessments that sought to differentiate between professional, subelite, and amateur *badminton* players just from their stroke performance. Similar approaches and methods were used in [30], where authors devised a system with three IMUs attached to the hand, wrist, and elbow of the athlete. The system employed deep learning methods for providing useful information to coaches in *table tennis* practice. Among racket sports, tennis seems to be the most popular for using inertial sensor systems. Yang et al. [31] used two IMU devices attached to the wrist and the knee of the athlete to evaluate the *tennis* serve performance through the support vector machine method. Very similar goals were presented in [32], where authors used three gyroscope sensors attached to the hand, upper arm, and chest of the athlete. They used DSP, statistical, and simulation methods for the assessment of the first serve skill in tennis. Stroke detection and classification were the main result of the paper [33]. The authors used a wrist-worn IMU and decision tree machine learning methods to detect and classify three most common tennis strokes: forehand, backhand, and serve with 98.1% accuracy. Human movement coordination assessment with the use of three IMUs at the hip, wrist, and chest of the athlete was presented in [34]. The authors evaluated *the baseball swing* movement based on the template matching method and give feedback to the athletes and coaches. Capturing fast athletic biomechanics was the core of the work presented in [35], whereby IMUs were positioned on the chest, upper arm, wrist, hand, and waist to acquire high dynamic movements with the combination of the multirange accelerometers and gyroscopes. For the high-dynamic movements, the accelerometers and gyroscopes with $\pm 200\ g_0$ and $\pm 20000^\circ/s$ were used, respectively. For the low-dynamic movements, the accelerometers and gyroscopes with $\pm 16\ g_0$ and $\pm 1000^\circ/s$ were used, respectively. The result of their work was a wearable dual-range sensor platform that enabled an investigation of high-level, very wide dynamic-range biomechanical parameters describing the baseball swing.

Team sports are also very interesting for research but may get complex because of the interactions, unpredictability, and nonuniformity of athlete actions. Studies of the sport activities in group sports were mostly limited to isolated specific movements of one athlete. Wang and colleagues [36] used one IMU at the wrist of the athlete to assess the skill level of a *volleyball* spiker. The recorded data was classified into three levels: elite, subelite, and amateur volleyball players with 94% accuracy. *Basketball* was also popular with researchers; Ma et al. [37] and Meng et al. [38] used a wrist-worn sensor to recognize and classify basketball movements using support vector machine classification methods. In [37], nine kinds of basic basketball movements, such as stand, walk, run, jump, in situ dribble, dribble while walking, dribble while running, set shot, and jump shot, were recognized. Shankar et al. [39] described the mobile system that enabled remote monitoring of shooting form of a basketball player. One IMU was attached to the wrist of the athlete that collects shooting data, and a heuristic classification method was used to estimate the shooting performance according to the efficiency calculated as the ratio of the shots made to the total number of shots taken by the player in a given range of flick velocities and loading angles. Results show that the player's shooting action improved and became more consistent within his preferred trajectory over the course of 3 weeks of training with the device. With wider use of machine learning algorithms in team sports, new possibilities of detecting and identifying group events at training and matches have become possible. Chambers and colleagues [154, 155] have designed algorithms based on the random forest for automatic detection of tackle, ruck, and scrum events in rugby union. During the match play, they achieved the classification accuracy of 79.4% (ruck), 81.0% (tackle), and 93.6% (scrum).

The next group of activities is sports where athletes move themselves with the aid of different equipment. We chose to report a few studies within the group of *skiing sports*, where athletes use different forms of skis to perform the desired action. The authors of [40] used deep learning techniques to analyse the data from 17 IMU devices attached to the *cross-country* skier. The result was the classification of the eight classical and skating style cross-country techniques based on the data from 5 most relevant IMUs with the accuracy of 87.2% and 95.1% for the flat and natural course, respectively. *Ski jumping is* an interesting winter sport discipline from the perspective of measurement of kinetic and kinematic parameters. Bessone et al. [42] used 11 IMUs to determine the possible correlation between kinematics and kinetics during landing. Analysis methods included DSP, statistics, and iSEN system software. The results can be used during daily training, giving specific feedback on the ways of reducing the vertical ground reaction force at landing. The most complex and dynamic of the studied winter skiing sports is *alpine skiing*. Analysis of motion of the lower extremities during the carving technique is performed in [43], where authors used 17 IMUs placed over the skier's body. The acquired data was processed and analysed by DSP algorithms, motion analysis capture system, and multiscale computer simulation. Fasel et al. [44] used 6 IMUs to capture the three-dimensional body and centre of mass kinematics of an alpine skier, with this IMU data augmented by a differential GPS system giving the location of the skier's COM on the skiing slope. Yu and colleagues [45] studied the potential of using IMU sensors for performance analysis of alpine skiers. They used 16 IMUs to find the best location of the sensor. The findings, based on the statistical analyses and the hierarchical clustering methods, suggested that the best location was the pelvis, as this may quite accurately reflect the total body's COM position.

From a number of implementation perspectives, the most challenging activities for the application of inertial units are *water sports*. For example, wearable sensor devices must be waterproof; therefore, their design and construction are more challenging and expensive. Also, radio signals do not penetrate water well; therefore, wireless communication with a sensor device underwater is practically impossible. Wang et al. [46] used one 9 degree-of-freedom IMU to capture the posture of the human lumbar spine during swimming. In order to quantify the spinal motion during swimming, they used an orientation estimation algorithm and a human

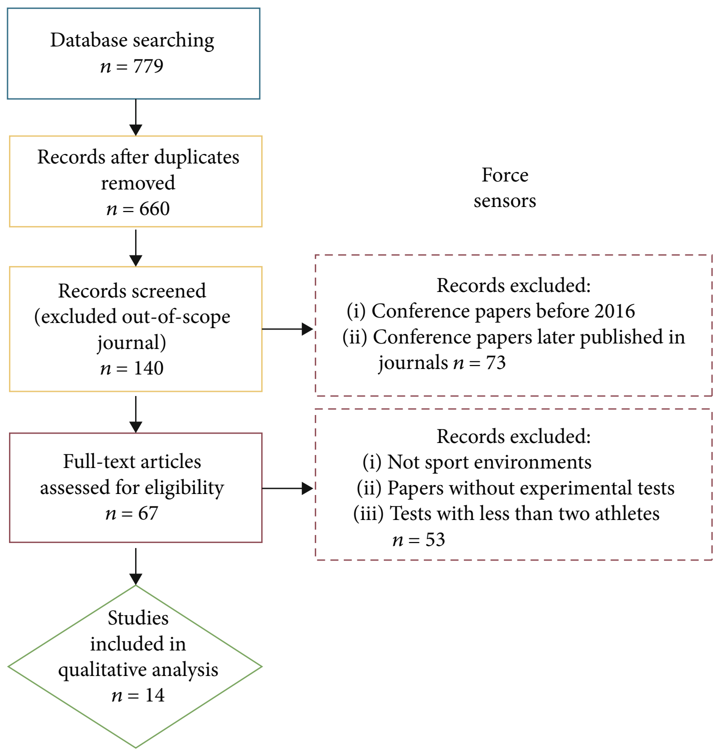

Figure 2: Selection process of papers focused on force sensors. Blue block represents the identification step, yellow blocks the screening step, red blocks the eligibility step, and green block the inclusion step.

biomechanical model. Their sensor system collected the data offline and transferred it wirelessly to the PC after swimming, when the swimmer gets out of the water. Lecoutere and Puers [47] used a low-power wireless sensor network and wearable sensor device attached to the head of the swimmer to track elite swimmers in real-time. Their wearable sensor device uses gyroscope and accelerometer signals to calculate the most important swimming parameters locally and sends them to the PC at the times when the swimmer's head is out of the water. A similar approach was performed by Kos and Umek [7], where one IMU with an accelerometer and gyroscope was attached to the low back to acquire a number of the most relevant swimming parameters for all four swimming disciplines. Their sensor device recorded the swimming data offline and transfers them to the PC after swimming using a wired connection.

3.2. Force Measurement Devices. Forces acting on (or generated by) an athlete can provide valuable insight into their likely performance and injury risk. Variables based on stand-alone force measurements include centre of pressure (CoP) [50], direction of the force as a proxy measure of efficiency [51], and impact forces [52]. Combined with kinematic measurements, force data have been used to estimate mechanical power [53], joint kinetics [43, 54], and muscle forces [55]. Analysing kinetics in the laboratory is mostly done with force plates which are typically embedded in the floor. This setup is however static and often does not allow the kinetics to be assessed during the actual sporting activity due to the inability to instrument the playing surface with a sufficient number of force platforms. Measurements of forces in sport applications therefore require wearable force measurement devices or specifically instrumented surfaces such as starting blocks in swimming or athletics which can only provide data on the race start. The selection process for paper inclusion is reported in Figure 2.

Table 3: References of force measurement based on different analysed sports.

Sport	Number of studies	References
Ice hockey	1	[50]
Baseball	1	[51]
Karate	1	[52]
Skiing	2	[43, 70]
Speed skating	3	[54, 60, 61]
Field hockey	1	[57]
Kayaking	3	[56, 62, 68]
Horse riding	1	[67]
Golf	1	[69]

Table 3 shows the distribution of the included studies based on the specific sport.

The literature on wearable force devices can roughly be divided into studies that use commercially available (off-the-shelf) pressure sensors and studies that use custom-built devices. Articles were selected in which the wearable systems were used in a setting that evaluated the biomechanics of athletes.

3.2.1. Commercially Available Systems. Pressure sensors are commercially available measurement devices that can be directly applied in an experimental sport setup. A list of commercially available devices used in literature is reported in Table 4. Pressure sensors convert physical pressure into an electric current or voltage. To estimate force, the pressure is multiplied by the area over which that pressure is applied. The number of sensors (how much target area is covered by the sensors) is therefore an important determinant for the accuracy of the system. Apart from the number of sensors, accuracy of the individual pressure sensors is determined by resolution, hysteresis, repeatability, and linearity. In the case of insoles, fit inside the shoes is important. In skating and skiing, shoes are often tight fitting, custom made, and thermoformed, which requires insoles that are customizable, for example, with the option to cut them in the right shape. A limitation of pressure sensors is that they measure the pressure only in one direction. A major advantage of these portable sensors is that they can be used in many different environments and sports.

As regards the evaluation of the CoP, Buckeridge et al. (2015) used insoles (Pedar X, Novel, Munich, Germany) to determine the CoP and foot pressure in elite and recreational ice hockey players in acceleration and steady-state forward skating. Although the plantar forces measured by the insoles were not different between elite and recreational athletes, a finding consistent with speed skating studies [58, 59], the CoP was different between the level of athletes. Elite players had their CoP more to the forefoot compared to recreational players during steady-state skating [50]. Although in this study only forward skating was considered, this measurement setup with insoles is applicable for the assessment of other locomotive activities performed in ice hockey games.

As regards the evaluation of the joint kinetics, two studies in literature used pressure insoles (Pedar X, Novel, Munich, Germany) in combination with an MVN motion capture suit comprising 17 IMUs (Xsens, Enschede, The Netherlands) to analyse joint kinetics in skiing [43] and short-track speed skating [54]. Combining kinematics from the Xsens suit with the measured plantar forces from the pressure insoles, an inverse dynamics analysis was performed to obtain the joint kinetics (intersegmental rigid body kinematics). Lee et al. [43] showed that hip, knee, and ankle joint forces and moments, calculated based on a standard inverse dynamics analysis using the motion capture data and ground reaction force, for middle-turn were higher compared to those for short-turn in ski carving. Purevsuren et al. [54] concluded that short-trackers have high internal rotational moments when the knee is flexed. This conclusion might however not be valid since pressure insoles can only estimate the force component normal to the plantar surface and hence moment (free moment) and force components parallel to the plantar surface. Instead, forces in the horizontal plane are significant in short-track speed skating [60]. Moreover, only straight forward skating was incorporated in the analysis, whereas most of the time skaters are either entering, exiting, or inside a curve [60]. The researchers may have been limited in measuring this part of the rink due to the high centrifugal forces that disturb the IMU-based measurement systems [61]. Apart from inaccuracies in force measurement, IMU-based (joint) kinematics are more inaccurate than optoelectronic measurement systems, which are currently regarded as "*gold standard*" [12]. In speed skating, a sensitivity analysis of joint power estimation using an inverse dynamics model of a speed skater showed that the model was most sensitive to the COM position of the trunk and the lean and steer angle of the skates (rotating the locally measured forces into a global frame). A 5° inaccuracy of the skate's steer angle, which is likely to occur in IMU-based systems [61, 156], resulted in approximatively 9.5% maximum error in the joint power estimations compared to optoelectronic systems. It should also be acknowledged that the inverse dynamics approach, even in laboratory situations, has some limitations relating to a variety of assumptions (e.g., use of rigid body segments) that may result in errors of approximately 10–20%. The reliability and value of this combination of systems for sport performance enhancement may still be somewhat limited.

As regards contact forces, commercially available pressure sensing components have also been integrated into custom arrangements for force sensing in specific applications. Jennings et al. [57] created a linear array of individual force-resistive pressure sensors (Flexiforce, A201-25, Tekscan) mounted to the head of a field hockey stick to measure the forces and CoP between the ball and stick during a goal shooting skill called a drag flick. The study determined that force and location of the ball along the stick were important for controlling the trajectory of the ball during the drag flick, and the simple sensing array was able to distinguish the skill level among athletes based on consistency of the force patterns and decreasing overall contact time [57].

An alternative to the insole systems discussed above, shoes or footplates may be instrumented with a custom arrangement of sensors. Sturm et al. [56, 62] mounted a rectangular array of individual force-resistive pressure sensors (Flexiforce, A201-100, Tekscan) to measure foot force transfer from kayaking athletes into the boat. In kayak racing, foot force has an important effect on the whole-body rhythm/movement pattern used to "kick" the boat forward, and this is evident in the alternating push-pull force displayed within each foot and also by the 180° phase difference in force timing between left and right feet.

3.2.2. Custom Systems. While pressure sensors are valuable for assessing normal force distributions, they cannot measure out-of-plane forces. Several studies have therefore constructed custom measurement devices to examine forces in three dimensions. Constructions usually incorporate commercially available load cells or strain gauges.

3.2.3. Instrumented Impact Plates. In the classic sense of a wearable device, Saponara [52] developed a wireless instrumented plate designed to be worn within the athlete clothing for measuring contact force during martial art sparring. The system comprised a matrix of strain gauge sensors to sense deformation of a thin aluminium plate under load from a kick or punch. Depending on the specific sport usage, several

Table 4: Variety of commercially available pressure insoles used in sport studies. Characteristics are based on data sheets provided by the manufacturers and via direct contact with the manufacturers where necessary.

Company	Product name	Technology	Measuring range (kPa)	Number of sensors (#)	Sam. Freq (Hz)	Recording time (h)	Thickness (mm)	Weight (g)	Wireless	Costs (€)
3L Labs	Footlogger	—	nk	8	500	24	3	Unknown		<1000
Moticon	OpenGo	Capacitive	500	16	100	0.5-16	3.2	116 (incl. battery)	X	1k-5k
Novel	Pedar X	Capacitive	600/1200	99-256	80-200	4.5	1.9	400 (incl. data box)		>10k
Orpyx	Kinetyx	Resistive	nk	37	256	12	nk	Unknown	X	1k-5k
SPI	Tactilus HP	Resistive	200	128	300	nk	1.3	Unknown		5k-10k
Tekscan	F-scan	Resistive	517/862	954	500	2	0.4	332 (incl. data box)		>10k

nk = unknown.

plates could be worn on the chest, shoulders, legs, and arms and linked by a microcontroller (HX711, Sparkfun) and Bluetooth to a single data acquisition program. They tested their system with a broad range of karate athletes, measuring contact time and force of strikes. The authors defined two performance metrics (kick-strength-to-weight ratio (KSWR) and punch-strength-to-weight ratio (PSWR)) and gave feedback to athletes using a grading scale from poor to excellent. The authors found a correlation between system measurements, effectiveness of leg/arm movement, and athlete skill level (i.e., years of experience). The authors suggest that the coordinative skill of the more experienced athletes allows them to more efficiently utilise the kinetic link principle, thereby ensuring a greater transfer force through the kinetic chain to the feet and hands when performing kicks and punches [52].

3.2.4. Instrumented Speed Skates. Although skates had been instrumented prior to 2010 using strain gauges [63–66], van der Kruk et al. built the first wireless instrumented speed skates for short-track (fixed blade) [60] and long-track (klapskates) [58] speed skating. The instrumentation is located in the bridge (klapskates) and cups (fixed blade) of the skates, each consisting of a sandwich construction that clasps piezoelectric three-component force sensors (Kistler 9602, Kistler Group, Winterthur, Switzerland). This allows measurement of the lateral and normal forces on the skates. The output of the sensor is logged on a SD card and sent over Bluetooth via a data logger that is attached to the skates. The instrumented short-track skates were used in the routine training of Olympic athletes. Within this homogenous group, higher-ranked male skaters tended to have a CoP more to the rear of the blade and lower lateral forces for several phases (curve, leaving the curve, and entering the straight) of skating [60]. Females showed a trend towards applying higher body weight normalised lateral forces than males, while skating at lower velocities, which is suggested to reflect body weight, muscular strength, and/or motor control differences between females and males while skating on the same blades [60]. Since lateral forces and the CoP determine the heading (steering) of the skate, this seems to be an important performance indicator that can be tracked with these wearable force platforms. Limitations for the current design of these skates are the additional weight, and, in the case of the instrumented short-track skate, the slight height difference may alter the feel and performance of the typical movement.

3.2.5. Instrumented Saddle. Analogous to [43, 54], Walker et al. [67] combined 5 IMUs (Xsens, Enschede, The Netherlands) to record gross body movement with axial load cells mounted within the stirrups of a horse racing saddle, underneath the jockey's feet. They compared the kinematics and kinetics of jockeys while galloping on a riding simulator with actual horse racing. The authors found that stirrup force amplitudes on real horses were more than twice those recorded on the simulator and were asymmetric, with higher peak forces applied to the stirrup opposite the horse's lead leg while the jockey's pelvis displaced laterally away from the lead leg, suggesting that jockeys use their legs and hips to isolate their centre of mass and dampen the effects of the horse's movement [67].

3.2.6. Instrumented Baseball. Often in ball sports, a strictly wearable device does not provide all the information of interest. This is especially true in ball throwing sports, like baseball, where a pitcher's choice of pitch type dictates finger position around the ball and effects the forces imparted by the fingers onto the baseball and the resulting trajectory of a pitch [51]. Kinoshita et al. (2017) embedded a triaxial load cell (USL06-H5-500N-C, Tec Gihan Co., Kyoto, Japan) in a Japanese league regulation baseball and recorded timing and amplitude of finger forces during fastball pitches. The embedded transducer was wired by a quick release mechanism to a data logger worn on the athlete's wrist, such that the connection would detach when the ball left the pitcher's hand [51]. The authors found that all fingers generated a peak force amplitude 37-43 ms before ball release, while the index and middle fingers displayed bimodal force patterns with an additional peak 6-7 ms before ball release. Peak ball reaction force exceeded 80% of maximum finger strength, and there was a linear relationship of peak force with ball velocity. Because of space limitations within the ball, they were unable to record all finger forces simultaneously. Instead, the hand was carefully repositioned between trials such that the appropriate finger of interest would overlay the force sensor. This does however introduce the possibility of crosstalk, which the authors acknowledge as a study limitation.

3.2.7. Instrumented Paddles. In kayaking, the athlete's paddle acts effectively as an extension of their arm for force generation. Providing feedback to athletes and coaches about the magnitude and shape of paddle force-time curves at different paces can have implications for performance and training. Two research groups [56, 68] independently developed paddle-mounted force systems where the shaft was instrumented with two sensor nodes, each comprising strain gauges (HBM, Darmstadt, Germany) in a Wheatstone bridge configuration. The FPaddle system developed by Gomes et al. [68] used 2 strain gauges directly bonded to the carbon fibre composite paddle with nodes located 80 cm from each blade tip, while Sturm et al. [56, 62] created a self-contained system with 4 strain gauges bonded to a cantilever beam and held in place on the paddle by a clamp mechanism. Gomes et al. [68] showed that on-water force-time profiles change in magnitude and shape with the increased stroke rate, with higher mean paddle force more strongly correlated with increased kayak velocity than peak paddle force. The authors also reported an efficiency metric—the ratio of mean force to peak force—which reflected shape changes in the force-time profiles and related this to stroke impulse (i.e., the integral of the force-time profile).

3.2.8. Future Implications. In addition to limitations of data transfer bandwidth and sampling rate, studies utilising customised external equipment still indicate that the ecological validity of these studies is still not perfect. Specifically, athletes were still aware of the additional weight in the

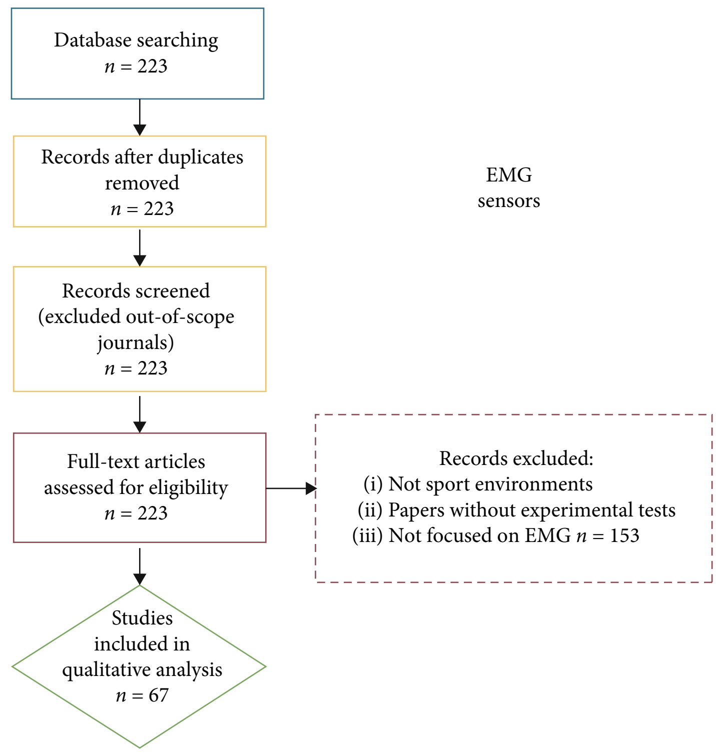

Figure 3: Selection process of papers focused on EMG sensors. Blue block represents the identification step, yellow blocks the screening step, red blocks the eligibility step, and green block the inclusion step.

equipment and concerned that this may lead to performance reductions, meaning the implementation of these tools in competition scenarios may not be currently advisable. Jennings et al. [57] noted that additional instrumentation mounted to the field hockey stick may effect ball contact and trajectory. Kinoshita et al. [51] quantified the decline in ball velocity (11% of self-reported max speed) as a function of the added load cell weight, which as a result could not be used in a regulation match. The authors also discussed concerns about impact forces of the ball against a bat or catcher's mitt and the potential for fatally compromising the instrumentation. Lastly, as with all on-water, ice, or snow-oriented sensor packages, waterproofing electronics is necessary but can be expensive and heavy, and if the sealing was to become compromised, also potentially hazardous [56, 60, 68].

3.3. Surface Electromyography. The applications of surface electromyography (sEMG) in sport science have become increasingly common and diversified in the last decade [157]. Possibly also thanks to the advent of wireless systems, sEMG is nowadays largely used not only as a descriptive tool but also in quantitative studies as well. Bipolar (i.e., employing a set of two electrodes) setups are popular in sport science to record noninvasively the summation of action potentials over the skin, giving as output an analogue signal that describes the electric potential difference (voltage) detected between the two electrodes [157]. Through specific postprocessing procedures, such as rectification and filtering of the signal, researchers can use multimuscle sEMG recordings to describe and/or quantify coordinated activations orchestrated by the central nervous system (CNS) to produce and control movement [71–137]. Of the 67 studies considered in this section, around half followed classic approaches for the analysis of sEMG [71–74, 76–115], leading to the computation of amplitude, timing, and frequency parameters. Another 31 adopted the muscle synergy framework to analyse the data [75, 116–136]. The selection process for the paper inclusion is shown in Figure 3.

3.3.1. Amplitude, Timing, and Frequency Content of sEMG. The most common approach to the analysis of sEMG signals is the assessment of the maximum or mean amplitude of the envelope, with or without normalisation to the maximum voluntary contraction [71–74, 76–87, 89–95, 97–106]. The analysis of timing is also common in sport science, with usual approaches ranging from the detection of the onset and offset of sEMG activity and global and local maxima detection to examination of the entire time course using statistical parametric mapping [72–74, 76–79, 81, 83, 89–93, 96, 100, 102]. Other advanced approaches include the analysis of the signal's frequency content, especially for fatigue estimation [79, 106], classification of sEMG patterns through k-means clustering or support vector machines [82, 88], and nonlinear analysis of the signals using the Lyapunov exponents [102]. The majority of the studies included the recordings of less than nine muscles [72, 73, 77–85, 87, 91–95, 98–106, 158], while only a few considered a number between nine and 16 [74, 76, 86, 88, 90, 96] or bigger than 16 [71, 97]. Most of the studies considered muscles of the lower limb

Table 5: References of electromyography applications based on different analysed sports.

Sport	Number of studies	References
Running	19	[83, 84, 89, 90, 92, 93, 95, 96, 111, 113, 116, 118, 123, 126, 127, 129, 130, 133, 136]
Resistance training or weightlifting	13	[78, 80, 81, 85, 86, 94, 97, 102, 103, 105, 108, 125, 128]
Cycling or handcycling	12	[71–76, 104, 109, 112, 114, 119, 124]
Swimming	5	[82, 87, 91, 106, 131]
Softball, baseball, or cricket	4	[98–101]
Rowing	2	[120, 134]
Golf	2	[88, 117]
Rugby or American football	2	[77, 137]
Cross-country skiing	1	[79]
Gymnastics	1	[135]
Ice hockey	1	[132]
Pole vaulting	1	[107]
Skateboarding	1	[115]

[71–73, 77, 78, 81, 83–85, 89, 90, 92, 93, 95, 96, 98, 104, 106, 115], with the remaining focussing on the trunk and/or upper limb [74, 76, 80, 82, 87, 94, 100, 102, 103, 106] or both the upper and lower body [79, 86, 88, 91, 97, 99, 101]. Bilateral recordings (involving the left and right hand side of the same muscles) were less common [71, 74, 77, 82, 86, 88, 90, 97, 98, 101] than ipsilateral [72, 73, 76, 78–81, 83–85, 87, 89, 91–96, 99, 100].

3.3.2. Muscle Synergies. The concept of muscle synergies is based on the fact that the CNS must constantly deal with an overabundant number of degrees of freedom [159]. Based on the seminal work of Bernstein [159], Bizzi and colleagues proposed that the CNS might simplify the production and control of movement by activating muscles in groups rather than individually, in common patterns called synergies [160]. Even though a direct experimental proof for this theory is currently missing, muscle synergies are increasingly being used in sport science to either speculate on the physiological meaning of coordinated muscle activation patterns or present multimuscle sEMG recordings in a compact way. Muscle synergies are in fact obtained by the factorisation of sEMG signals, a numerical procedure that allows for the reduction of dimensionality of big data sets through decomposition techniques such as nonnegative matrix factorisation (NMF), principal component analysis (PCA), independent component analysis, and factor analysis [116, 127, 161]. All of these methods reduce sEMG time series to a set of motor modules (time-invariant muscle weights), which describe the relative contribution of single muscles within a specific synergy and a set of motor primitives (time-dependent coefficients), representing the common activation patterns. Studies on the reliability of muscle synergy extraction in relation to sport activities are scarce but nevertheless present in the considered literature [108, 116, 127, 128]. The most common family of algorithms used to reduce the dimensionality of the data was NMF [107, 108, 110–114, 116–125, 127–133, 135–137], with a few studies also using PCA to extract synergistic muscle activations [75, 109, 126, 134]. The total number of muscle activities recorded varied heavily across the considered studies. We found a range in the number of muscles recorded across these studies, including one to eight [108, 109, 124, 126, 131, 133], between nine and 16 [75, 107, 110–114, 116, 119, 121–123, 125, 128, 130, 132, 134–137], and between 16 and 25 muscles [117, 118, 120, 127, 129]. Bilateral recordings were less common [107, 108, 117, 119, 129] than ipsilateral [75, 109-114, 116, 118, 120–128, , 128, 130–137]. Most of the studies considered muscles of the lower limb [75, 108, 109, 112–114, 116, 119, 123, 124, 126, 130, 133, 136], even though almost as many muscles are included from the trunk and/or upper limb as well [110, 111, 117, 118, 120, 125, 127–129, 131, 132, 134]. Only three studies focused exclusively on the upper body [107, 135, 137].

3.3.3. Sport Application with EMG. The studies considered analysed a rather broad spectrum of sport activities (Table 5). The most represented activity was running, although this was assessed in a variety of conditions including overground or on treadmill, shod or barefoot, level or incline, at different speeds, and on even or uneven surfaces [83, 84, 89, 90, 92, 93, 95, 96, 111, 113, 116, 118, 123, 126, 127, 129, 130, 133, 136]. A lot of attention was also given to resistance training or weightlifting [78, 80, 81, 85, 86, 94, 97, 102, 103, 105, 108, 125, 128] and to cycling or handcycling [71–76, 104, 109, 112, 114, 119, 124]. Swimming is also getting increasing interest in recent years [82, 87, 91, 106, 131] as are ball sports such as softball, baseball, or cricket [98–101]. We found that less attention was given to sports such as rowing [120, 134], golf [88, 117], rugby or American football [77, 137], cross-country skiing [79], gymnastics [135], ice hockey [132], pole vaulting [107], and skateboarding [115]. Among those studies, it is interesting to notice how the use of sEMG to quantify injury risk or recovery is still very limited [81, 88, 90, 104].

There is, however, a new branch of sport science that employs perturbations as either the pivotal component of training interventions or the mean to investigate the responses of the CNS in balance-challenging conditions. Perturbation has to be intended as a change of movement, as reported in the Oxford dictionary. Perturbations can be used to uncover motor control processes that under unperturbed circumstances would not be available for observation [162]. Of the six studies that dealt with perturbations, four have been published after March 2017, indicating an increasing interest in the topic by the sport science community [97, 102, 103, 110, 121, 136]. A brief review of those six works is presented in the following lines. Kohler and colleagues calculated the average root mean square (RMS) of the sEMG signal recorded from eight ipsilateral muscles of the upper limb and trunk while lifting stable (barbell) and unstable (dumbbell) loads on stable (bench) and unstable (Swiss ball) surfaces in a seated overhead shoulder press [103]. They found the highest RMS values of the *triceps brachii* sEMG activity when lifting the stable load on a stable surface, while the lowest values were associated with lifting of unstable loads on an unstable surface. Based on those observations, the authors concluded that training interventions centred on lifting overhead unstable loads and/or surfaces might not benefit the development of core muscle strength. A similar conclusion was also drawn in another study that reported no significant correlation between three measures of core muscle strength and the difference in dumbbell overhead shoulder press strength when assessed on a stable bench compared to an unstable Swiss ball [163]. In a similar fashion, Nairn and colleagues analysed the amplitude of the linear envelope of the sEMG signals recorded from 12 bilateral muscles of the trunk and lower limbs during a squat exercise while lifting stable (Olympic bar) and unstable (water-filled cylinder, only on a stable surface) loads on stable (solid ground) and unstable (BOSU ball) surfaces [97]. The authors found that unstable loads on stable surfaces reduced the activation of the *erector spinae* but increased the activation of the *abdominal external oblique* compared to stable loads. However, lifting stable loads on unstable surfaces increased the activation of more distal muscles, such as *gastrocnemius medialis*, *biceps femoris*, and *vastus medialis*. The conclusion from this study was that altering the stability of the support surface and/or the stability of the load to be lifted can have differing effects on the muscle activity of the agonist compared to stabiliser muscles. Lawrence and colleagues set out to investigate the stability of sEMG signals recorded from eight bilateral muscles of the trunk and upper limbs during bench press involving stable (standard barbell) and unstable (flexible barbell with loads suspended by elastic bands) loads [102]. The authors calculated the Lyapunov exponents of the sEMG signals but did not specify if they computed the short- or long-term exponents. They concluded that unstable loads were managed by reducing the instability of sEMG signals (i.e., lower Lyapunov exponents). de Brito Silva et al. extracted synergies from the muscle activity of 12 lower limb muscles recorded during single-leg landing from a lateral jump on a stable surface [121]. Then, they proceeded to train the participants on an unstable surface (wobble board) three times a week for four weeks and assessed the effects of training on muscle synergies. The authors reported a modified modular organisation of muscle activation patterns after wobble board training, but no changes in the number of muscle synergies. Specifically, the landing strategy switched to a separation of the relative contribution of the plantarflexors (*gastrocnemius medialis* and *gastrocnemius lateralis*) from the dorsiflexors and mediolateral stabilisers (*tibialis anterior* and *peroneus longus*, respectively). Moreover, the relative contribution of secondary muscles within each motor module decreased. The authors concluded that wobble board training modifies the modular organisation of landing redistributing the relative contribution of muscle groups in a function-specific way. Oliveira and colleagues analysed the influence of perturbations (translation of support surface) on the modular organisation of direction changes during running [110]. The setup consisted in recording the sEMG activity of 16 ipsilateral muscles of the lower limb and trunk during 90° side-step cutting manoeuvres while running with and without translation of the solid support surface at contact. The results showed no differences in the number of muscle synergies and minor effects of perturbations on motor modules, while motor primitives underwent stronger modifications. The authors concluded that the timing properties of motor primitives were likely influenced by sensory input and descending command integration. Santuz et al. investigated the effects of terrain morphology on the modular organisation of running [136]. The experimental setup consisted of a standard and an uneven-surface treadmill, on which the participants ran while the sEMG activity of 13 ipsilateral muscles of the lower limb was recorded. Similar to the studies of de Brito Silva et al. and Oliveira et al., the authors found that the number of muscle synergies was not affected by the uneven surface. Moreover, the changes in the motor modules due to the challenging terrain were subtle. The changes in the motor primitives, however, were visible in the weight acceptance and propulsion synergies. Specifically, the primitives of those two synergies were significantly wider in the uneven surface as compared to the even surface condition. The authors concluded that the widening might be a strategy adopted by the CNS to make chronologically adjacent primitives overlap. This would increase the robustness (i.e., ability to cope with errors) of the motor output when locomotion is challenged by external perturbations.

Taken together, these results show that perturbations can be used to study those motor control processes that under unperturbed circumstances would not be available for observation. This allows for a better understanding of a complex system such as the CNS not only from a basic research point of view but also from an applied research perspective as well. The studies mentioned above highlight the specific role of the perturbation type and location in modulating the activity of determined muscle groups [97, 103, 121] and how activation patterns are modulated by the CNS in challenging settings [102, 110, 136]. Perturbation-based studies and training interventions are becoming ever more popular, and researchers as well as coaches will likely benefit, in the near future, from a wider body of literature.

4. Conclusions

The assessment of motor performance in sports is becoming more and more important due to the high level of competition and financial rewards among athletes. Wearable sensors have the potential to provide key data relating to training and competitive performance. Among other sensor options, inertial sensors are the most widespread, even though force measurement systems and electromyography allow further information on the kinetics, and associated muscle activity levels can provide additional insight into the motor behaviours of athletes. From the analyses, it should be also underlined that some methodologies, for example, the computation of joint moments from the pressure insoles, need to be validated before they are more commonly used in the field of sport biomechanics to ensure that such data is methodologically solid, meets the metrological requirements (accuracy, reliability, and repeatability), and is meaningful for the field of sport biomechanics. The outcomes of this literature review provide sport scientists (including biomechanists), coaches, and athletes an overview on sport biomechanics applications that required the use of wearable sensors.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Research Article

Application of an Accelerometric System for Determination of Stiffness during a Hopping Task

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Currently, there are several computational methods for stiffness during a hopping task, but they do not necessarily yield the same values. Therefore, it is essential that the simplicity of the equipment used does not affect the measurement validity. The aim of this study is to compare the stiffness values during a hopping task recorded in a laboratory environment and those acquired using the Myotest accelerometer. The measurements were performed on a group of 30 untrained female students (age: 23.0 ± 1.7 years, body height: 1.72 ± 0.07 m, and body mass: 64.8 ± 10.0 kg). According to the manual for the Myotest accelerometric system, each study participant performed three sets of 5 hops. Vertical stiffness was determined based on two measurement methods, one using the Myotest accelerometer and the other using Kistler force plates. The mean value (±SD) of vertical stiffness was 19.0 ± 9.3 kN/m in the countermovement phase and 15.1 ± 5.9 kN/m in the take-off phase. Furthermore, the stiffness determined using the Myotest was 30.7 ± 13.3 kN/m. However, significant relationships between the vertical stiffness in the countermovement phase and the Myotest stiffness ($r = 0.79$) and between the vertical stiffness in the take-off phase and the Myotest stiffness ($r = 0.89$) were found. The relationships between the vertical stiffness (in the countermovement and take-off phases) and the stiffness estimated using the Myotest allow us to conclude that despite the significantly overestimated stiffness value, the Myotest accelerometer can still be used for determination of the stiffness trends, e.g., following training. The overestimated stiffness values can result both from inaccuracy in the determination of ground contact time and flight time by the Myotest accelerometer and from the use of an equation that assumes that the movement of the center of mass has a harmonic profile.

1. Introduction

Evaluation and monitoring of biomechanical variables have become an important element in the quantitative analysis of athletic performance. Sports coaches will obtain valuable information from measurements carried out under conditions as close as possible to those during competitions. Therefore, they are often skeptical of analyses performed under isolated laboratory conditions. However, recent technological innovations related to the miniaturization of wearable sensors that do not influence the technical movements of athletes allow movement analysis to be performed during sporting activities. An example of a tool that allows the measurement of acceleration during motion and under training conditions is the Myotest performance measuring system (Myotest SA, Sion, Switzerland).

The Myotest accelerometric system is a wireless handheld device weighing just a few ounces (59 g) and is attached to a specially designed belt at the pelvic level. This 3-D accelerometer allows the estimation of variables such as jump height, time of contact, reactivity, and stiffness during a hopping task. Time of contact refers to time when the feet (at least one) are in contact with the ground between the flight phases. Reactivity should be understood as the reactive strength index (RSI), i.e., as the ratio of jump height to contact time [1]. We can also find in the Myotest guide that "*muscular rigidity*, *which is* *usually called stiffness, is an interesting indicator enabling you to find the ideal muscular tension for bouncing in running events or team sports, for instance*." However, the problem of the "stiffness" estimated by the Myotest seems more complex than this definition.

Stiffness is a quantitative measure of the elastic properties of the body and is expressed as a ratio of the deforming force to the deformation length (most commonly in relation to longitudinal deformation) [2]. Therefore, stiffness represents the measure of resistance to strain and is described as an essential factor in the optimization of human locomotion [3–5]. Dalleau et al. [6] argued that stiffness is also related to the maximal performance of single and cyclic movements. When hopping, the human body (movement of the center of mass) resembles a bouncing ball. Therefore, the term "*bouncing gait*" has been used to describe the human body during hopping tasks where lower limbs perform the function of "*springs*" responsible for center of mass (COM) movements [4, 5, 7]. Therefore, a hopping human body can be modeled by using a simple spring-mass model that contains a single (linear and massless) "*leg spring*" and a point that represents the total body mass [3]. Leg stiffness (defined as the ratio of changes in the ground reaction force to the respective changes in "*spring length*" representing both lower limbs) and vertical stiffness (defined as the ratio of changes in the ground reaction force to the respective vertical displacement of the COM) are commonly used to describe the mechanical properties of a "*spring*" representing the lower limbs during a hopping task [8].

The Myotest guide does not give an unambiguous answer as to which of the above types of stiffness (leg or vertical) is the value provided by the Myotest accelerometric system during the hopping test. Some authors equate the stiffness value estimated by the Myotest with leg stiffness [9–12]. However, the accelerometer is not capable of measuring the change in "*spring length*." Moreover, estimations of stiffness using an accelerometer also do not provide insights about the ratios of stiffness in individual joints. Therefore, it should be assumed that the stiffness value estimated by the Myotest is vertical stiffness. The Myotest accelerometric system is recognized as a reliable and valid tool for the estimation (despite significant overestimation) of jump height based on the flight time method [13–17]. However, it seems that the problem of the stiffness determined using an accelerometer is currently not properly investigated. To our knowledge, only a few studies [9, 10] have raised the issue of stiffness estimated by the Myotest.

In the process of sports training control, it is necessary to quantify the effects of the exercises and loads applied. Therefore, the use of a portable measuring device is a compromise between measurements under laboratory conditions and those under training conditions. However, there are currently several computational methods for (vertical) stiffness, but they do not necessarily yield the same values [8, 18–20]. Therefore, it is essential that the simplicity of the equipment used does not affect the measurement validity. The aim of this study is to compare the stiffness values during a hopping task recorded in a laboratory environment and those acquired using the Myotest accelerometer.

2. Materials and Methods

The measurements were performed on a group of 30 untrained female students from the University School of Physical Education. They were persons with no competitive-level sports training (within a period of at least 5 years before the experiment) and with no injuries to the musculoskeletal (motion) system. The study group was characterized by the following mean parameters (±SD): body height: 1.72 ± 0.07 m, body mass: 64.8 ± 10.0 kg, and age: 23.0 ± 1.7 years. The tests were carried out in the Biomechanical Analysis Laboratory (with PN-EN ISO 9001: 2009 certification). Each subject completed all trials in the same time period of test days (in the morning) to eliminate any influence of circadian variation. Subjects refrained from physical activity for 24 hours before testing, to avoid any interference in the experiment. Prior to the measurements, the participants were familiarized with the purpose of the study and gave written consent for participation in the experiment. Before the test, the subjects were informed of the activities they were supposed to perform and were motivated to properly perform the task. The research project was approved by the Senate's Research Bioethics Commission, and the procedure complied with the Declaration of Helsinki regarding human experimentation. We followed the methods of Struzik and Pietraszewski [21].

Each study participant performed three sets of 5 hops (hopping test). The measurement procedure was conducted in accordance with the Myotest performance measuring system: quick start guide (jump–plyometry test). The trials were simultaneously recorded by the Myotest accelerometric system (Myotest SA, Sion, Switzerland) and by two force plates (9286A, Kistler Group, Winterthur, Switzerland). The sampling frequencies of the signal from the force plates and the accelerometric system were set at 500 Hz. This sampling frequency is the maximum common value for both systems. The use of force plates is usually considered the gold standard [13, 15].

Prior to the measurements, a 10-minute-long warm-up, which included jogging (shuttle runs over a distance of 10 m, at a moderate pace of ca. 10 sections per minute), a series of hops, and a familiarization test task, was administered. Each study participant started performing a trial series after becoming familiar with the test. After the trial series, the proper research procedure began. Next, the participant was asked to perform a series of 5 bilateral hops (3 sets) from the standing position to the maximum height (performed as a bounce action on the fore foot) and with minimal time of contact with the ground. The whole part of the hopping test took place on a rigid surface (force plates). As indicated by the guide, the participant wore a belt with the Myotest accelerometer attached vertically on the left side of the body at the pelvic level (fastened around both greater trochanters of the femurs and the medium part of the gluteal region). Before each trial, the subjects were asked to stand over the force plates (each foot on a separate plate) while assuming a vertical posture with arms akimbo, looking straight ahead and standing still (Figure 1). The hopping test instructions given were as follows (according to Myotest guide): "*at the short beep from accelerometer*, *perform a countermovement*

Figure 1: One of the participants standing on the force plates with the belt to which the Myotest accelerometer is attached vertically on the left side of the body at the pelvic level.

jump, then bounce back up five times as high as possible and with a ground contact time that is as short as possible, while keeping your hands on your waist (*jump off the soles of the foot with minimal bending of the knees, like on a trampoline*)." After 5 hops, the participant reassumed a vertical standing posture, and the double beep from the accelerometer signals the end of the test. During the experiment, the participant was asked to rest her palms on her hips to exclude the effect of arm swing on hopping performance. Landings were performed on the same plates as take-offs. According to the Myotest guide, a one-minute rest took place between test repetitions. Errors in hopping task execution are signaled by a deep beep from the accelerometer. The Myotest accelerometric system tolerates two errors before automatically stopping the test. An error message is generated if the following points are not observed (according to Myotest guide): "(1) *execute the movements energetically so that the Myotest can clearly detect them*, (2) *stand still before the starting beep*, (3) *ground contact time must be short and clearly below the time of flight, and* (4) *perform a total of 5 bounces*." During performance of the hopping test, the participant should take-off with the knees and ankles extended and land in a similarly extended position. The test was repeated if the lower limbs were flexed at the knee and/or hip joints during the flight phase (incorrectly performed hopping task).

Further analysis focused on the attempt with the highest mean height of hops obtained by each participant. From the hopping task, 5 hops were analyzed without taking into account the starting countermovement jump. The values of all presented variables were averaged for the five analyzed hops to obtain results analogous to those obtained from the Myotest. The hopping test was used with some simplifications that resulted from the use of the spring-mass model, which characterizes both running and hopping. The model assumes that the human body consists of a material point representing the total mass of the body; a massless "spring" representing both lower limbs, which performs the supporting function; and a parallel source of force resulting from the active action of the muscles involved in the take-off [3]. Based on the vertical ground reaction force (F) recorded by the force plates (the ground reaction forces registered by both force plates were added up), it was possible to determine the flight time (t_f) and ground contact time (t_c) during the hopping task. The instantaneous pattern of changes in the height of the COM (y) was calculated by double integration of the COM vertical acceleration, as calculated from the vertical ground reaction force [4]. The vertical (quasi-) stiffness ($K_\mathrm{v} = \Delta F/\Delta y$) of the human body during the hopping task was determined as the ratio of the change in the ground reaction force (ΔF) to the corresponding change in the height of the COM (Δy) separately for the countermovement and take-off phases, similar to the method described by Struzik and Zawadzki [22]. To reliably estimate vertical stiffness, it is necessary to determine the relationship $F(\Delta y)$ shown in Figure 2. The slope coefficient for part of the curve $F(\Delta y)$ equals the numerical value of stiffness in this range. Vertical stiffness was calculated for the parts of the countermovement and take-off phases where the slope of the F curve with respect to the Δy axis was relatively constant and the $F(\Delta y)$ profile was nearly linear. For the countermovement phase (marked green in Figure 2), this range was the part between the moment of landing on the plates and the lowest location of the COM (Δy_{max}). The boundaries of the part for the take-off phase (marked blue in Figure 2) were represented by the local maximum of the ground reaction forces (point F_{max} from which ground reaction forces decreased only) and the moment of take-off from the plates [22]. This observation holds true only if the value of the coefficient of determination R^2 that expresses the quality of adjustment of the trend line to the relevant part of the $F(\Delta y)$ curve is sufficiently high (over 0.6) [23]. If the points Δy_{max} and F_{max} occur at exactly the same time, then the whole $F(\Delta y)$ curve is analyzed. If not, then the part of the $F(\Delta y)$ curve between the Δy_{max} and F_{max} points (marked in black in Figure 2) is omitted to maintain the maximum possible linearity of the studied parts of the countermovement and take-off phases. It is possible that the $F(\Delta y)$ curve intersects [7], for example, in the upper part, as shown by Choukou et al. [9], which causes the F_{max} point to appear before the Δy_{max} point. Then, the profile of the F (Δy) curve should be considered individually, and the boundary of the analyzed parts of the countermovement and take-off phases should be modified. For example, the

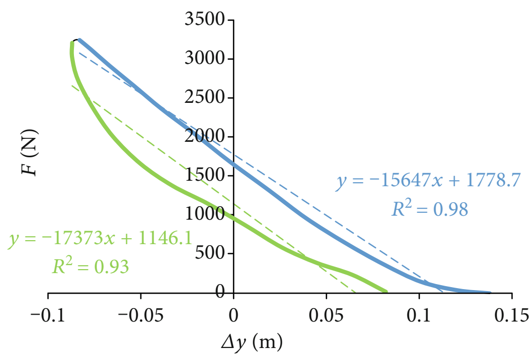

Figure 2: Ground reaction force depending on the COM vertical displacement for one of the study participants during the hopping test (for one of the hops), along with trend lines and equations that describe these dependences for the parts of the countermovement (marked green) and take-off phases (marked blue) and the values of coefficients of determination R^2.

analyzed countermovement phase part will end at the point $F_{\max}$, and the analyzed part of the take-off phase will begin at the point $\Delta y_{\max}$.

The Myotest accelerometer was used to record the following variables during the hopping test: jump height (h_{Myo}), ground contact time ($t_{\text{c-Myo}}$), and stiffness (K_{Myo}). In the Myotest guide, the manufacturer did not explain how the values of individual variables are estimated. However, based on the accelerometer capabilities, one can guess that the values of jumping height (h_{Myo}) and ground contact time ($t_{\text{c-Myo}}$) were determined based on the duration of the flight and ground contact phases [9]. Based on the jump height (h_{Myo}) recorded by the Myotest accelerometer, the flight time ($t_{\text{f-Myo}}$) could be determined using the following formula:

$$t_{\text{f-Myo}} = 2 \cdot \sqrt{\frac{2 \cdot h_{\text{Myo}}}{g}}, \quad (1)$$

where g is the acceleration due to gravity [24]. Furthermore, (vertical quasi-) stiffness ($K_{\text{v-Myo}}$) can be evaluated using the equation described by Dalleau et al. [6], which assumes that the curve reflecting the ground reaction force versus time is a part of the sine wave:

$$K_{\text{v-Myo}} = \frac{m \cdot \pi \cdot \left(t_{\text{f-Myo}} + t_{\text{c-Myo}}\right)}{t_{\text{c-Myo}}{}^2 \cdot \left(\left(\left(t_{\text{f-Myo}} + t_{\text{c-Myo}}\right)/\pi\right) - \left(t_{\text{c-Myo}}/4\right)\right)}, \quad (2)$$

where $K_{\text{v-Myo}}$ is the vertical stiffness, m is the body mass, $t_{\text{f-Myo}}$ is the flight time, and $t_{\text{c-Myo}}$ is the ground contact time. Therefore, it may be accepted that the stiffness value estimated by the Myotest is the vertical (quasi-) stiffness.

The sample size was determined based on the power analysis. For $n = 30$, the power of applied statistical tests $(1 - \beta)$ is close or equal 1. The Shapiro-Wilk (W) and Lilliefors tests were used to examine the distribution of individual variables. All the studied variables had a distribution close to normal. Therefore, parametric tests were used for further analyses. Pearson's r correlation coefficient was used to evaluate the concurrent validity of the Myotest accelerometric system and force plate. The significance of the correlation coefficient value was verified with the t-test. To demonstrate possible differences between the values of the variables obtained from different measuring devices, Student's t-test of significance of differences for dependent variables was used. In all tests performed, the level of significance was set at $\alpha = 0.05$. Statistical calculations were made by means of the Statistica 13.3 software package (TIBCO Software Inc., Palo Alto, CA). Furthermore, the remaining calculations were made using a Microsoft Excel 2016 spreadsheet (Microsoft Corporation, Redmond, WA). Additionally, concurrent validity was analyzed through a Hopkins [25] spreadsheet to quantify the relationship between the practical (Myotest) and criterion (force plate) measures. The validity spreadsheet is based on simple linear regression to derive a calibration equation, a typical error of the estimate, and Pearson's r correlation coefficient. The criterion was the dependent variable, and the practical was the predictor in a consecutive pairwise manner. The typical error of the estimate was standardized (SEE) by dividing by the SD of the criterion. SEE was evaluated using half the thresholds of the modified Cohen scale: <0.1, trivial; 0.1–0.3, small; 0.3–0.6, moderate; 0.6-1.0, large; 1.0-2.0, very large; and >2.0, extremely large. Uncertainty in the estimates was expressed as 90% confidence limits. To complement the correlation analysis, Bland-Altman plots were used to visualize the mean of the difference (bias) and the limits of agreement (95% confidence intervals).

3. Results

The mean value (±SD) of vertical stiffness was 19.0 ± 9.3 kN/m in the countermovement phase and 15.1 ± 5.9 kN/m in the take-off phase during the hopping test. Furthermore, the stiffness determined using the Myotest accelerometric system was 30.7 ± 13.3 kN/m. Therefore, the stiffness values determined using the Myotest were significantly higher than the stiffness values determined using the force plate in both the countermovement ($\Delta = 11.7 \pm 8.2$ kN/m) and take-off phases ($\Delta = 15.6 \pm 8.5$ kN/m). However, significant relationships between the vertical stiffness in the countermovement phase and the Myotest stiffness ($r = 0.79$, SEE $= 0.77$, Figure 3) and between the vertical stiffness in the take-off phase and the Myotest stiffness ($r = 0.89$, SEE $= 0.50$, Figure 4) were found. A significant difference between the vertical stiffness values in the countermovement phase and those in the take-off phase ($\Delta = 4.0 \pm 5.7$ kN/m, $p < 0.001$) was also found.

Bland-Altman plots are presented in Figures 5 and 6. For any measurement system to be valid, most of the paired differences should lie within the 95% limits of agreement, whereas their mean can help identify whether any system underestimates or overestimates measurements relative to the criterion (bias). The results indicate that the Myotest accelerometric system overestimated measurements of stiffness during the hopping test. In Figures 5 and 6, 28 of the 30 analyzed measurements are within the limits of agreement. However, significant relationships between the paired

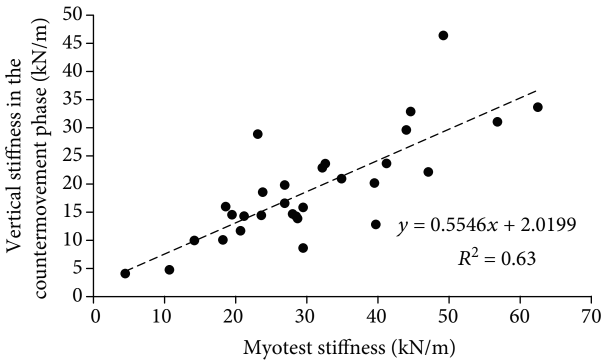

FIGURE 3: Vertical stiffness in the countermovement phase versus stiffness determined using the Myotest accelerometric system during the hopping test with an equation describing the trend line and the value of the determination coefficient R^2.

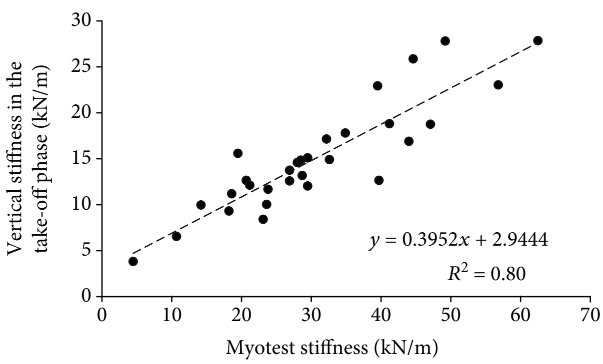

FIGURE 4: Vertical stiffness in the take-off phase versus stiffness determined using the Myotest accelerometric system during the hopping test with an equation describing the trend line and the value of the determination coefficient R^2.

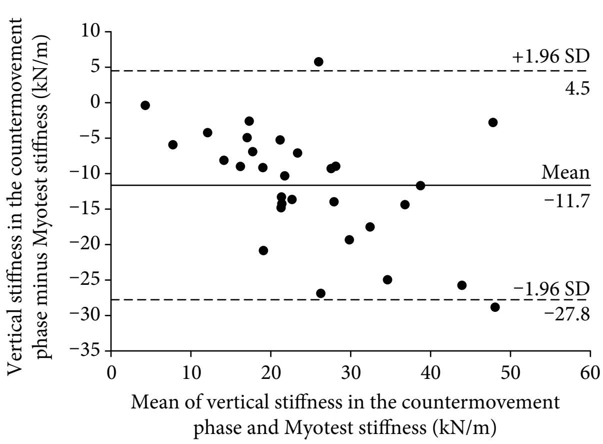

FIGURE 5: Bland-Altman plot of the force plate (in the countermovement phase) and Myotest stiffness (95% limit of agreement is 16.1 kN/m).

differences and means were found, indicating that the bias is not constant over the entire range. Therefore, as the Myotest stiffness value increases, the vertical stiffness estimation error in the countermovement ($r = -0.51$) and take-off phases ($r = -0.90$) also increases.

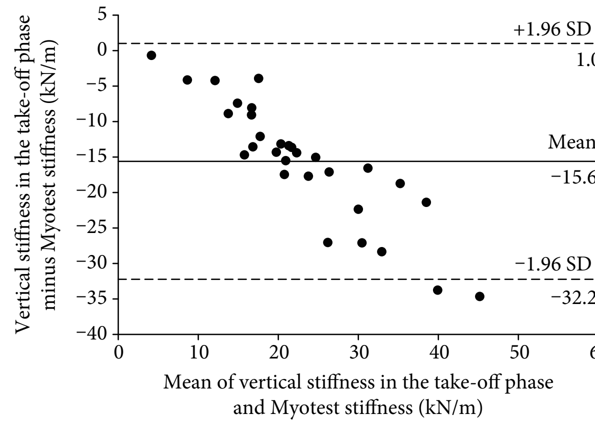

FIGURE 6: Bland-Altman plot of the force plate (in the take-off phase) and Myotest stiffness (95% limit of agreement is 16.6 kN/m).

Table 1 contains the mean values (±SD) of ground contact time and flight time obtained with the Myotest accelerometric system and force plate. The ground contact time estimated by the Myotest was significantly shorter than that obtained from the force plate measurements. In turn, the flight time estimated by the Myotest was significantly longer than that obtained from the force plate measurements.

Moreover, the value of stiffness determined using the force plate time measurements (t_c and t_f) and the equation described by Dalleau et al. [6] was $K_D = 15.6 \pm 5.7$ kN/m. K_D was significantly lower than the vertical stiffness in the countermovement phase ($\Delta = 3.4 \pm 5.2$ kN/m, $p < 0.01$) and the Myotest stiffness ($\Delta = 15.1 \pm 8.4$ kN/m) and was at a similar level as the vertical stiffness in the take-off phase.

4. Discussion

Although popular motor ability tests can be performed in a simple manner and under any conditions (for example, the Sargent vertical jump test), modern measurement equipment provides more accurate information about a particular ability or variable. The development of technology also allows a more objective and precise evaluation. It is also becoming easier to collect more data than was previously possible using conventional methods and tools. Therefore, it is fundamental that coaches should utilize available methods for applying scientific output in sports training. Utilizing these methods is likely to provide them with feedback on the current skill level of an athlete and the efficiency of the particular practice stimuli used and will help them plan future training programs. Modern measurement tools also offer possibilities for the detection of irregularities in an athlete's body that might lead to injuries.

Reliability can be defined as the consistency of measurements (test-retest) [13]. Choukou et al. [9] and Ruggiero et al. [10] stated that the stiffness values estimated using the Myotest accelerometer showed a high level of reliability. On the other hand, validity refers to the ability of a measurement tool to reflect what it is designed to measure [13]. However, the problem of validity of stiffness measurements using Myotest is much more complex and not yet fully explained.

Table 1: Mean values (±SD) of ground contact time (t_c) and flight time (t_f) obtained with the Myotest accelerometric system and force plates.

	t_c (s)	t_f (s)	$t_c + t_f$ (s)
Myotest	0.18 ± 0.06	0.51 ± 0.03	0.68 ± 0.07
Force plate	0.25 ± 0.07	0.44 ± 0.04	0.69 ± 0.07
Δ	−0.08 ± 0.01*	0.07 ± 0.02*	−0.01 ± 0.01

Δ represents differences between the values of times obtained with the Myotest accelerometric system and force plates. *Statistically significant at $p < 0.05$.

Both the laboratory and field tests must be valid and reliable in order to properly use information obtained on their basis. Therefore, laboratory measuring systems [26–28], portable measuring tools [29–31], calculation methods, and measuring movements [8, 20, 24, 32–34] are subject to verification. Compared to other devices for field-based jumping evaluation, the Myotest has the advantages of being small and portable, easy to handle, relatively cheap, able to provide immediate results, and usable on particular surfaces (e.g., on the sand), which allows measurements under any conditions without limitations on the measurement space [13, 14]. However, it cannot be used during a game or competition [35].

The stiffness determined using the Myotest accelerometric system during the hopping test was significantly higher than the vertical stiffness determined using the force plate measurements in the countermovement and take-off phases. Therefore, the Myotest overestimated measurements of stiffness, as in other studies [9, 10]. Choukou et al. [9] noted significantly higher values of stiffness estimated by the Myotest (by 7.8 kN/m) during the hopping test than the vertical stiffness values determined using a force plate. The stiffness estimation method during hopping presented by Dalleau et al. [6] assumed that the curve that describes the dependence of the ground reaction force on time is a part of the sine wave and therefore that the COM motion is harmonic. However, this method is only the first half of oscillations, as a result of which it does not strictly meet the assumptions of harmonic motion. The description (equation) is appropriate for the steady course of such oscillations. Notably, the method presented by Dalleau et al. [6] can cause the values of vertical stiffness to be significantly overestimated, especially at relatively low hopping frequencies. Based on the given hopping test instruction and the obtained t_c and t_f values, it can be concluded that the hopping frequency chosen by the participants in this study was low.

On the other hand, Hobara et al. [20] reported that the stiffness estimation method presented by Dalleau et al. [6] significantly underestimates vertical stiffness values during hopping compared to those obtained from other calculation methods. However, Hobara et al. [20] took all measurements on a force plate without using the accelerometer. In this study, the values of stiffness determined using the force plate measurements (t_c and t_f) and the equation described by Dalleau et al. [6] were also significantly lower than the vertical stiffness values in the countermovement phase and the Myotest stiffness values and were at a similar level as the vertical stiffness values in the take-off phase. The overestimated stiffness value by the Myotest accelerometer during the hopping test can therefore result from inaccuracy in the determination of ground contact time and flight time. These two variables are mainly responsible for the stiffness value estimated using the equation presented by Dalleau et al. [6]. In this study, the ground contact time estimated by the Myotest was significantly shorter than that obtained from the force plate measurements. In turn, the flight time estimated by the Myotest was significantly longer than that obtained from the force plate measurements. The trends in the mentioned differences coincide with those presented by other authors [9, 13]. Choukou et al. [9] stated that the measurement of ground contact time by the Myotest during the hopping test is nonvalid. The most accurate devices for recording vertical jump flight time and ground contact time are force plates, which allow precise identification of the instant of take-off (the point at which the feet lose contact with the ground and the value of vertical ground reaction force drops to zero) and instant of landing (the feet land in the same position as take-off). It is assumed that the COM height at take-off is relatively the same as that at landing [24]. The Myotest estimates flight time using the time difference between the positive (during take-off phase) and negative (during landing phase) peaks of vertical velocity. However, the maximal positive vertical velocity is reached shortly before the instant of take-off, and the maximal negative vertical velocity is reached shortly after the instant of landing. Therefore, the flight time recorded by the Myotest accelerometer is overestimated, and the ground contact time is underestimated [9, 13, 24]. The ground contact time and flight time values presented in Table 1 confirm the above assumptions, which can significantly distort the stiffness values estimated by the Myotest during hopping.

A significant relationship between the vertical stiffness in the countermovement phase and the Myotest stiffness obtained during hopping was found. This relationship was very high but also had a large SEE. A significant relationship between the vertical stiffness in the take-off phase and the Myotest stiffness was also found. This relationship was very high and had a moderate SEE. When the SEE is large, the predicted y values are scattered widely above and below the regression line (Figures 3 and 4). However, based on the Bland-Altman plots (Figures 5 and 6), most of the paired differences are within the 95% limits of agreement. Therefore, it can be concluded that the Myotest accelerometric system is valid but overestimates the vertical stiffness values during hopping. Moreover, greater overestimation is observed with an increase in the criterion value. Therefore, the Myotest stiffness is not interchangeable with respect to the values obtained from other measurement devices and methods. The Myotest accelerometric system determines an approximate value that can provide information about only changes in vertical stiffness during the hopping test.

Determination of the vertical stiffness during the hopping task requires several assumptions that sometimes seem to have been omitted, whereas measurement validity would require verification of these assumptions. The simplest case is when F_{max} occurs exactly at the same time as Δy_{max}.

Without this synchronization, it would be necessary to determine which of these events occur first and, consequently, to modify the equation to reproduce the profile of the $F(\Delta l)$ curve as accurately as possible. The increase in the ground reaction force with respect to the COM displacement should be linear or close to linear over the whole duration of the contact with the ground phase. If the moment of occurrence of $F_{\max}$ divided t_c into two halves (harmonic movement), it would theoretically mean the same values of vertical stiffness during the countermovement and take-off phases. Meeting the above conditions would justify using one value as vertical stiffness for a specific movement while neglecting the calculations for the take-off phase [36]. Ferris and Farley [4] emphasized that during hopping, $F_{\max}$ and $\Delta y_{\max}$ do not necessarily occur at the same time. It is assumed that for a hopping frequency lower than 2 Hz, lower limbs stop behaving as linear springs, thereby distorting the $F(\Delta l)$ profile [7, 37]. In this work, the vertical stiffness values in the countermovement phase were significantly higher than those in the take-off phase. Therefore, to fully understand the phenomena occurring during human motion, it seems necessary to determine the vertical stiffness for both phases of motion separately. The assumption that the value of vertical stiffness in the countermovement phase is always the same as that in the take-off phase may be too much of a simplification. Luhtanen and Komi [38] estimated vertical stiffness during running and long jump with a division into the eccentric and concentric phases. Furthermore, the stiffness determined based on observation during motion should be viewed as quasi-stiffness, i.e., the ability of the human body to resist external displacements while ignoring the temporal profile of the displacement. Vertical stiffness is not stiffness viewed in strict terms due to the substantial contribution of other factors (such as damping and inertia) that affect the $F(\Delta y)$ relationship, especially during transient states [2].

Despite the clearly established procedures for hopping test performance and Myotest accelerometer fixation, between-subject differences in hopping technique (differences in jumping technique due to gender [23, 36, 37, 39] and sports training [36, 40–42]), elastic belt fastening and positioning around the hips, and, consequently, Myotest orientation may cause unexpected device displacements during hopping. Because the Myotest was applied vertically to an elastic belt, the accelerometer may have moved forward a certain amount during the countermovement or take-off phase due to trunk flexion. This movement would have caused vertical acceleration, and consequently, the vertical velocity and time (ground contact and flight) recordings would present a certain amount of random error [13]. It seems that stable fixation on the dorsal portion of the pelvic girdle of the jumping person can provide less sensitivity to undesirable accelerometer movement [30, 43, 44]. As a result, Castagna et al. [15] and Choukou et al. [9] decided to place the Myotest accelerometer in such a way.

A certain limitation of this study can be the studied group of untrained female. Based on other studies [36], it can be expected that the absolute stiffness value will be higher for male than for female and higher for athletes than for untrained people. Therefore, according to the relationships presented in this paper (between the paired differences and means), even larger bias values (larger overestimation of vertical stiffness values by the Myotest) can be expected in groups of males and athletes.

5. Conclusions

The relationships between vertical stiffness (in the countermovement and take-off phases) and the stiffness estimated using the Myotest accelerometric system allow us to conclude that, despite the significantly overestimated value of stiffness, the Myotest accelerometer can be used for determination of the stiffness trend. Therefore, this measurement device offers only an approximate stiffness value that can provide information about changes, e.g., following training. Therefore, the Myotest stiffness is not interchangeable with respect to the values obtained from other measurement devices and methods because of systematic overestimation. The overestimated stiffness value can result both from inaccuracy in the determination of ground contact time and flight time by the Myotest accelerometer and from the use of an equation that assumes that the movement of the center of mass has a harmonic profile.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

Part of this manuscript was presented at the 21st Annual Congress of the European College of Sport Science 2016 in Vienna, Austria.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Research Article

Using Wearable Inertial Sensors to Estimate Kinematic Parameters and Variability in the Table Tennis Topspin Forehand Stroke

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The study examined kinematic parameters and their inter- and intrasubject variability in the topspin forehand of seven top-level table tennis players. A wireless inertial measurement unit (IMU) system measured the movement of the playing hand to analyze the Ready position, Backswing, and Forward events, and a racket-mounted piezoelectric sensor captured the racket-ball Contact. In a four-phase cycle (Backswing, Hitting, Followthrough, and Back to Ready position), body sensors recorded the cycle and phase duration; angles in the sagittal plane at the shoulder, elbow, and wrist of the playing hand and at the knee joints; and acceleration of the playing hand at the moment of racket-ball contact. The coefficient of variation (CV) was calculated to determine the variability of kinematic parameters within and between players. The observed variability in stroke time duration was low (CV < 20%) indicating constancy. The small-to-medium intraindividual variability of angles (CV < 40%) indicates that each player used a broadly repeatable technique. The large intraindividual variability in movement was probably functional (i.e., motor adjustment and injury avoidance). Interindividual and intraindividual variability of knee and elbow angles was low; wrist extension was the most variable parameter (CV > 40%) for all tasks, and shoulder joint variability was medium-to-large. Variability in hand acceleration was low (CV < 20%). Individual players achieved relatively constant hand acceleration at the moment of contact, possibly because angular changes at one joint (e.g., shoulder) could be compensated for by changes at another (e.g., wrist). These findings can help to guide the teaching-learning process and to individualize the training process.

1. Introduction

Table tennis is a very fast, varied, and complex game, requiring an immediate response to changing stimuli. The difficulty of the game is increased by the high speed and variety of ball rotation [1, 2]. Multiple factors affect performance in this sporting discipline, including the level of technical preparation, tactical thinking, motor skills, mental preparation, and physiological determinants [3]. At an elite level, competition (match) outcomes are often determined by very small differences and sometimes by moments of excellent performance, and many table tennis coaches and professionals have identified comprehensive and perfect technique as a prerequisite for high-level success [4, 5]. In general, technique is thought to determine tactical potential and likelihood of achieving champion status [6].

There is evidence that the topspin forehand is among the most frequently used strokes in modern table tennis, in both the first attack and its continuation or counter-attack [7–9]. In this stroke, the velocity of the racket at the moment of contact with the ball reaches 20 m/s; following impact, the ball reaches a velocity of up to 45 m/s, rotating at up to 140 revolutions per second [1, 10, 11]. Theoreticians and practitioners regard the topspin forehand as a complex stroke, involving a kinematic chain of proximal-to-distal sequences or a stretch-shortening cycle. The speed at which the racket hits the ball is primarily influenced by hip joint and body rotation, flexion and adduction at the shoulder joint, and flexion at the elbow joint [12, 13]. During a game, the player must react to different situations and associated changes in ball parameters such as speed, rotation, flight trajectory, point of contact with the table, and height of rebound. In deciding on the type of stroke, the player adjusts their movements, the angle of the racket, the force applied, and the direction of racket movement. For example, a player attacking with topspin against a backspin shot and hitting the ball below the line (surface) of the table must "open" the racket, hitting the ball close to its central line and directing the movement from the bottom upward. In contrast, when returning a topspin ball flying above the net line, they must close the racket, hitting the upper part of the ball and directing movement strongly forward. Deciding on the type of stroke may also involve other changes—for example, from a rotational to a direct hit—resulting in further alteration of motion parameters.

This complexity means that players must choose from a range of options while maintaining high movement accuracy. It is therefore interesting to explore variations in table tennis players' movements and the limits of this variation. Within the rich literature on movement variation, some researchers have approached this as a problem of movement "noise"—that is, as nontargeted variability resulting from a complex multijoint movement [14]. However, it is increasingly suggested that this variability (both inter- and intraindividual) may be a functional and purposeful response to different situations and requirements of the task, such as parameters of the flying ball or avoiding injury [14]. Others have emphasized the need for consistency and repeatability; for example, Whiteside et al. suggested that a consistent projection angle during service is critical for successful tennis performance [15]. Small differences in movement parameters may also indicate a compensation mechanism, as for example when a change in the range of motion at one joint is compensated by a change at another [16–20]. According to some researchers, human movement variability facilitates motor learning through active nervous system regulation [21, 22]. Functional variability of movement is also thought to change and develop with player age and experience [23]. There is also evidence that variability decreases when movement is accompanied by increased mental focus on a particular aspect of activity [24].

As well as works investigating the kinematics of table tennis strokes [10, 12, 25], a number of studies on stroke kinematics have examined the relationships between movement and work done or force generated, between force and racket speed, and between the kinetics of the upper limbs and other body segments [13, 26, 27]. To the best of our knowledge, however, the issue of movement variability in table tennis kinematics has not yet been intensively explored. Among existing studies, Bootsma and van Wieringen [28] referred to movement variability in the accuracy and time of movement of five table tennis players during a drive stroke (which can be described for present purposes as "light topspin"). They found that when forced to play accurately—that is, to hit a specified target—the spatial and temporal accuracy of players' movement was reduced in attempting to hit the target. At the same time, variability at the moment of contact between racket and ball was also reduced—a phenomenon they characterized as "compensatory variability." In a study of racket kinematics and direction during the forehand drive stroke across different levels of expertise, Shepard and Lee also found that movement variation was reduced at the time of racket-ball contact [29]. They described this phenomenon as "funneling" and again noted the speed-accuracy trade-off.

It seems, then, that the mechanisms of movement variability in table tennis warrant more detailed investigation. In particular, it seems interesting to investigate the best table tennis players' use of the topspin forehand, which is the most commonly used stroke in the game. To guide the teaching-learning process and to individualize the training process, it seems useful to explore movement variability and the conditions and limits of its occurrence. This may assist in the process of monitoring and correcting technique and in developing improvement plans for individual players.

To that end, the present study employed inertial measurement unit (IMU) sensors from the myoMotion System to measure selected kinematic parameters of the topspin forehand stroke and the intra- and interindividual variability of these parameters among advanced male table tennis players. Specifically, we hypothesized that measurement of key kinematic parameters of the topspin forehand stroke (duration of the cycle and its phases and knee, shoulder, elbow, and wrist joint angles) would explain any variability in these strokes. We further assumed that the values of some of these parameters would vary more ($CV > 40\%$)—especially in the Ready position and Backswing phases—and that some would be less variable ($CV < 20\%$), especially the moment of contact and elbow and wrist joint angles, in light of the principle of "funneling" described in the literature.

2. Materials and Methods

The study participants were seven top adult male players from Poland's national team, with a mean body height of 177 ± 3.5 cm and mean body mass of 76 ± 8.5 kg. Each participant was informed about the purpose and nature of the research and signed an informed consent form. The study protocol was approved by the Institutional Ethics Board (Senate's Research Bioethics Commission at the University School of Physical Education in Wrocław). All the players ranked among the top ten Polish senior athletes. Six of the players were right-handed, and one was left-handed. Participants were asked to perform the topspin forehand stroke with submaximal or maximal force on a specially prepared stand (see Figure 1), and individual kinematic parameters of the players were measured using the MR3 myoMuscle Master Edition system (myoMOTION™, Noraxon, USA). To record acceleration, wireless IMU sensors were attached (as per the myoMotion protocol described in the manual) to the following body segments: head, left and right arms, left and right forearms, left and right hands, left and right thighs, left and right foot, shanks, and body trunk (see Figure 2). The myoMotion system includes a set of 1 to 16 inertial sensors; using so-called fusion algorithms, a 3D accelerometer, gyroscope, and magnetometer measure the 3D rotation of each sensor in absolute space in terms of yaw, pitch, and roll (also known as orientation or navigation angles). To record and

Figure 1: Research stand.

analyze the moment of racket-ball contact, a piezoelectric sensor (7BB-20-6L0, Murata Manufacturing Co., Ltd., USA) compatible with the myoMotion system was attached to the racket. The max sampling rate was 100 Hz per sensor for the whole 16-sensor set, and this was adjusted to the speed of registration by the piezoelectric sensor (1500 Hz). The maximum test range of the 3-axis digital accelerometer is $\pm 16g$ ($g = 9.8\,\text{m/s}^2$) with $10000g$ high shock survivability.

Prior to testing, the athletes completed the standardized general (15 minutes) and sport-specific (20 minutes) warm-up procedures. Each then performed a topspin forehand with maximum or submaximal force. Each task comprised 15 presented strokes, and the player was required to hit the marked area (30 × 30 cm) at the corner of the table. Every successful shot (i.e., "on table" and played diagonally) was recorded for further analysis. Any balls missed, hit out of bounds, or hit into the net were excluded. Balls were delivered according to specified parameters (see Table 1) by a dedicated table tennis robot (Newgy Robo Pong Robot 2050, Newgy Industries, Tennessee, USA; see Figure 1).

All movement parameters were recorded and calculated using a standard protocol and report of the myoMotion software. Focusing on the topspin forehand technique, assessment of variability was confined to joints on the playing side (shoulder, elbow, and wrist) and the knee joints, which have been identified as decisive for performance of the topspin forehand [12, 30, 31]. We chose to discuss only selected movements in sagittal plane where the ROM is greatest and the speed of movement has probably the greatest impact on the spin of ball. In order to show the magnitude of variation, we chose only selected parameters. The sensors attached to the athlete's body and to the racket recorded the values of the following parameters for further analysis: angles of playing hand, extension of the wrist, shoulder flexion, elbow flexion, and knee flexion (both sides), and acceleration of the playing hand at the moment of racket-ball contact. Movement of the playing hand was measured to assess the following specific events in the cycle: Ready position (racket not moving after previous stroke, before swing, forward-backward acceleration =0); Backswing (the moment at which the racket changes direction from backward to forward in the sagittal plane following the swing); and Forward (the moment at which the racket changes direction from forward to backward in the sagittal plane after the stroke). The fourth event in the cycle—the moment of ball-racket contact—was captured by the racket-mounted sensor. Each click on the racket (i.e., contact of racket and ball) transmitted a signal from the sensor to the system software. The moment at which this signal was registered was treated as the moment of racket-ball contact.

By capturing these events, it was possible to determine the duration of individual phases of the stroke: Backswing (Ph1); Hitting (Ph2); Followthrough (Ph3); and Back to Ready position (Ph4). It is also worth noting that the study confirms the utility of Noraxon's IMU as an alternative to optical motion capture systems for movement analysis. During dynamic trials, the root mean square error (RMSE) for myoMotion (as compared to Vicon) was 0.50 deg, with a correlation coefficient of 0.99 between Vicon and myoMotion for dynamic trials [32].

Using basic descriptive statistics (means, standard deviations, and variances) for all kinematic parameters, their variability was measured as coefficients of variation [33]. For the purposes of this study, low variability was defined as CV < 20; medium variability was defined as 20–40; and high variability was defined as CV > 40. Statistical calculations were performed using the Statistica software (Statistica 12.5, StatSoft Inc., Tulsa, USA).

3. Results and Discussion

Intraindividual and interindividual variability in the topspin forehand stroke was measured by coefficients of variation (CV), based on IMU values for the following kinematic parameters.

3.1. Time Duration. The results for temporal parameters are shown in Tables 2 and 3.

There was little variation in overall cycle duration across participants (Table 2). Of the four distinct phases, the Hitting phase (Ph2) was shortest in duration. Variability in the duration of individual hitting phases was small (CV < 20%) or medium (20–40%). Values in Ph4 (return to the Ready position) differed for every player and returned the most cases of CV > 40%. Among individual players, variability in duration of the entire cycle and its individual phases (Table 3) was small (total time TT), with CV values for all players ranging from 0.8% to 6.7% (Table 3). Low variability cases included Ph1 (one player), Ph2 (four players), and Ph3 (six players). The remaining cases in these three phases were characterized by medium variability. Based on these results, the large number of cases of low variability (low CV values) in individual athletes for the entire duration of the stroke (TT) and for most phases (mainly Hitting and Followthrough) indicates that variation in these parameters is small and that stroke characteristics are fairly constant, confirming the findings of previous studies [11, 13]. For each player, the greatest variation was observed in duration of Ph4 (Back to Ready position). The beginning of the Ready position phase (Ph4) was defined as the point at which

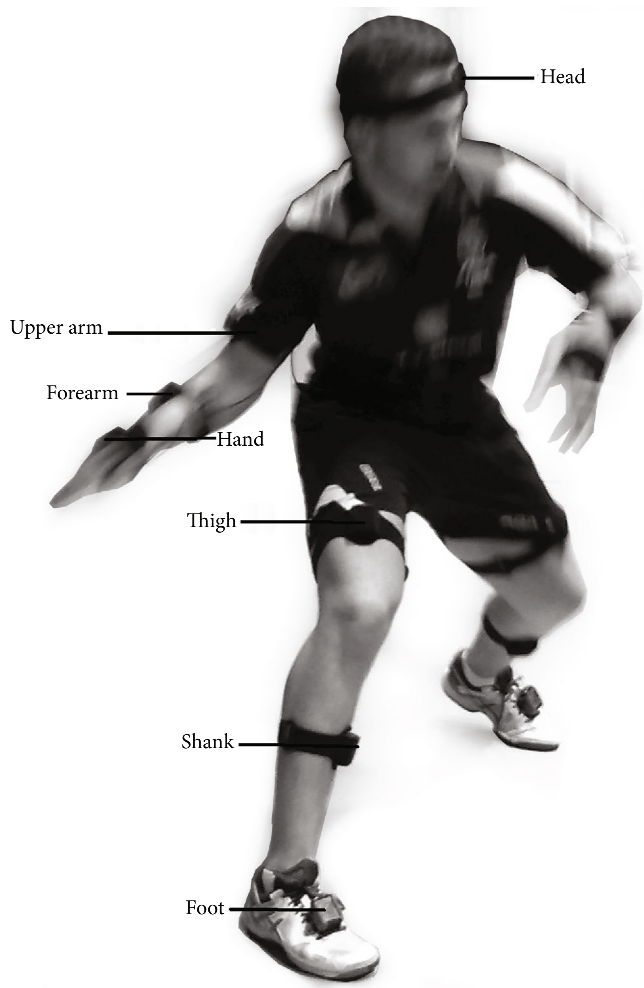

Figure 2: Sensor locations.

Table 1: Table tennis robot parameters.

Robot parameter	Value
Rotation (direction of spin)	Topspin
Speed (determines both speed and spin, where 0 is the minimum and 30 is the maximum)	18
Left position (left most position to which the ball is delivered)	4
Wing (robot's head angle indicator)	8.5
Frequency (time interval between balls thrown)	1.4

the player held the racket stationary before the next action ($\text{forward} - \text{back acceleration} = 0$) while waiting for the robot to deliver the ball. As this moment was freely determined by each participant, the duration of this phase varied more. Interestingly, the results across the entire group indicate small or medium variation in duration for most phases (Table 3) other than Ph4 (from Forward to Ready position), where variability exceeded 40%. This indicates that players' performance of the tasks was similar in terms of duration of the stroke and its individual phases.

Table 2: Time duration of particular phases during topspin forehand in the entire group of players ($n = 7$)—means, standard deviations (SD), variations (V), and coefficients of variation (CV).

Variable	Topspin forehand				
	Ph1	Ph2	Ph3	Ph4	TT
Mean (s)	0.5	0.1	0.2	0.4	1.5
SD (s)	0.1	0.0	0.0	0.1	0.0
V	0.0	0.0	0.0	0.0	0.0
CV (%)	18.3**	46.2	18.2**	25.7*	1.4**

Ph1: Backswing; Ph2: Hitting; Ph3: Followthrough; Ph4: Back to Ready position; TT: total time of the cycle. *Average variability. **Small variability. Not marked CV: high and very high variability.

3.2. *Angles.* The myoMotion system was also used to measure angles at joints known to be important for specific events during table tennis performance (see Tables 3 and 4). In the analysis of results for the entire group (intervariability), knee and elbow joints accounted for the highest number of cases of small variability (low CV value) (see Table 4). There were 8 cases of high or very high variability and 12 cases of small

Table 3: Variability (CV in %) of time duration of particular phases during topspin forehand in particular players (1-7).

Player	Topspin forehand Ph1	Ph2	Ph3	Ph4	TT
1	31.6**	10.0**	21.4*	107.8	2.3**
2	22.1*	36.8*	3.1**	65.9	1.1**
3	25.3*	36.0*	1.6**	79.9	5.0**
4	21.6*	13.8**	5.2**	64.4	0.8**
5	15.9**	15.5**	2.8**	63.7	0.9**
6	22.2*	30.8*	8.9**	65.2	6.3**
7	28.4*	9.2**	6.7**	80.1	6.7**

Ph1: Backswing; Ph2: Hitting; Ph3: Followthrough; Ph4; Back to Ready position; TT: total time of the cycle; *Average variability. **Small variability. Not marked CV: high and very high variability.

or average variability. In terms of intraindividual variability, the analysis indicates that individual variability of movement was low in 82 of 140 cases and medium in 19 cases (Table 5). Regarding individual events, there were some cases of high variability for all joints, most of which related to angles in the Ready position (6 of 35 cases) and at the moment of contact (14 of 35 cases) (see Table 4). High variability most often related to the position of the hand at the wrist joint on adopting the Ready position (2 of 7 cases), completion of the movement (Forward, 6 of 7 cases), and the position of the arm at the shoulder joint at the moment of Backswing (3 of 7 cases).

The analysis of angle variations in the four selected topspin forehand events (Ready position, Backswing, Contact, and Forward) focused on the CV values of the angles. Intraindividual variability was more often small or medium rather than large, indicating that the participating players each used a repeatable technique. As in other sports, however, it is impossible to state unequivocally that any given player repeated the same task with the same movement pattern. For example, in their review of research on interindividual and intraindividual variation in track and field throwing events, basketball throws, and gait during human locomotion, Bartlett et al. demonstrated that the large variation in movement is probably functional in character, as athletes make motor adjustments or seek to avoid injury [14]. They also noted that even the best athletes (with similar results) fail to perfectly reproduce the same movement (in terms of parameters, range of motion, and coordination). Bartlett et al. further argued that these factors should be considered when preparing an individualized training plan for each athlete, taking into account their unique capabilities. In the present context, that might include addressing the various ways of coordinating topspin movement and perhaps compensating for a small range of motion in one joint by ensuring a larger range of motion in another. Crucially, any coaching to shape and improve stroke technique should be flexible.

3.3. Acceleration and Compensatory Mechanism. The variability of acceleration values was small in all cases, both for the entire group and for individual players (Table 6). It is important to mention that the specified task required participants to use submaximal force. At the moment of contact, several players exhibited high or very high variability of angles, especially in extension at the wrist joint. There was also medium and high variability of the shoulder joint in many cases, but the variability of acceleration values remained low, perhaps because changes at the shoulder and wrist joints are mutually dependent—in other words, changes at one joint are compensated for by changes at the other. This kind of compensation mechanism has been observed in other studies and in other sports; for example, Button, MacLeod, Sanders, and Coleman evaluated movement variability in basketball players performing free throws [34] and found that players compensated for mutual changes of angle at the elbow and wrist joints. They further reported that variability at the elbow and wrist joints tended to increase toward the end of the throwing action. In a study of cueing actions in billiards (assessing parameters such as velocity, acceleration, height, and angle of the cue), Kornfeind et al. [35] observed significant variability in stroke movement despite very similar outcome values.

Many researchers have emphasized functional variability—that is, flexible changes in movement parameters in response to the changing requirements of the game or competition [14, 19, 36]. In the present case, the observed acceleration values may indicate similar functional variability and compensation mechanisms in table tennis. While angular variability at the joints was often low or medium in individual athletes, the frequency of high variability cases indicates that table tennis players' technique is not entirely repetitive. In contrast, there was very little difference in hand acceleration at the time of contact, with CV values well below 10%. Despite some angular variation in subsequent events, individual players (and the entire group) exhibited relatively constant hand acceleration at the moment of contact between racket and ball, indicating compensatory changes in angular parameters (e.g., shoulder/wrist) as observed in many other sports [16–19, 37, 38].

In sporting contexts, there is some evidence of the need for constancy and repeatability in the range of specific parameters [15]; in the present case, one such constant element was acceleration value at the moment of contact, with small CV values across the entire group. A similar phenomenon has been documented in billiards [36], golf [20], basketball [31], and by other authors [14]. The low CV values for acceleration at so important a point as racket-ball contact support the findings of Bootsma and Wieringen [29] and Shepard and Lee and Xie [30] regarding acceleration and reduced variability at critical moments.

Among the limitations of the present study, the sample was small ($n = 7$), and all of the participants were male, making it difficult to generalize the findings. Additionally, while this study examined only the topspin forehand with use of submaximum or maximum force, our recent work reports similar findings for other variants of this stroke [39]. A final limitation is that the present study was laboratory-based, and examination of variability in kinematic parameters under game condition might yield different outcomes.

Table 4: Values of angles at joints in chosen events during topspin forehand in the entire group of players ($n = 7$)—means, standard deviations (SD), variations (V), and coefficients of variation (CV).

	Ready position					Backswing					Contact					Forward				
	ShF	ElF	WrE	RKnF	LKnF	ShF	ElF	WrE	RKnF	LKnF	ShF	ElF	WrE	RKnF	LKnF	ShF	ElF	WrE	RKnF	LKnF
Mean (deg)	13.2	66.1	44.7	43.3	41.4	8.7	47.6	25.4	51.9	58.0	26.4	43.7	47.7	47.6	52.7	90.8	87.0	-3.0	51.1	49.7
SD (deg)	9.2	6.6	41.5	10.6	5.3	8.6	20.9	11.8	14.3	8.9	11.8	15.3	39.3	12.7	9.3	18.2	21.5	25.2	10.8	10.1
V	84.3	43.9	1727.8	111.5	28.1	74.9	435.0	139.3	203.6	78.7	139.1	232.8	1542.5	162.4	87.3	330.9	464.1	636.2	117.2	102.7
CV (%)	69.6	10.0**	92.4	24.4*	12.8**	99.2	43.8	46.5	27.5*	15.3**	44.6	34.9*	82.3	26.8*	17.7**	20.0*	24.7*	851.0	21.2*	20.4*

ShF: shoulder flexion; ElF: elbow flexion; WrE: wrist extension; RKnF: right knee flexion; LKnF: left knee flexion. *Average variability. **Small variability. Not marked CV: high and very high variability.

TABLE 5: Values of angles at joints in chosen events during topspin forehand of particular players (1-7)—means, standard deviations (SD), variations (V), and coefficients of variation (CV).

Variable		Ready position ShF	Ready position ElF	Ready position WrE	Ready position RKnF	Ready position LKnF	Backswing ShF	Backswing ElF	Backswing WrE	Backswing RKnF	Backswing LKnF	Contact ShF	Contact ElF	Contact WrE	Contact RKnF	Contact LKnF	Forward ShF	Forward ElF	Forward WrE	Forward RKnF	Forward LKnF
1	Mean (deg)	10.8	62.2	82.2	44.7	42.1	36.1	75.8	6.0	74.8	65.8	34.9	56.7	88.5	71.7	59.6	82.1	108.5	40.2	66.9	57.6
	SD (deg)	11.6	11.9	33.9	16.6	13.2	32.7	6.2	43.2	3.4	6.9	15.8	26.1	39.9	30.8	27.6	24.2	19.6	74.3	10.9	9.3
	V	135.1	141.2	1148.4	276.5	173.6	1067.2	38.6	1862.9	11.3	48.3	251.1	681.1	1593.4	947.4	759.6	586.3	383.7	5521.9	118.9	86.5
	CV (%)	147.7	19.0**	49.1	33.4*	28.1*	138.3	8.4**	185.9	4.5**	10.7**	55.7	55.4	54.8	54.3	55.3	32.3*	18.4**	308.3	16.9**	16.5**
2	Mean (deg)	18.5	80.3	40.0	59.5	40.2	0.6	58.1	31.6	70.6	71.6	17.2	61.0	62.1	64.3	70.4	70.2	72.2	-8.4	50.5	61.8
	SD (deg)	19.6	3.6	10.1	3.8	7.3	30.5	19.2	23.7	7.2	6.0	22.6	21.5	16.0	2.7	4.1	36.7	2.7	11.5	4.7	5.2
	V	386.0	12.6	103.0	14.2	53.1	930.5	370.3	563.8	52.0	35.6	509.8	463.6	255.5	7.3	16.7	1344.6	7.4	132.5	21.9	27.0
	CV (%)	144.6	4.4**	23.1*	6.4**	17.7**	931.5	35.04	88.0	10.4**	8.4**	181.5	41.5	24.1*	4.2**	5.8*	48.5	3.8**	131.3	9.0**	8.4**
3	Mean (deg)	17.2	68.8	33.9	38.1	50.0	11.5	67.5	40.4	47.9	57.7	-1.4	43.9	5.9	42.4	61.3	75.9	104.5	11.9	58.6	47.8
	SD (deg)	3.5	7.6	8.1	4.5	4.7	2.4	2.4	8.3	3.6	5.1	3.4	22.2	4.4	21.2	29.5	2.3	8.9	6.6	5.7	7.7
	V	12.2	57.1	65.5	20.0	22.2	5.6	5.7	68.9	12.6	26.4	11.6	493.9	19.6	450.0	871.6	5.2	78.9	43.9	32.6	58.5
	CV (%)	20.8*	11.1**	24.2*	11.3**	9.3*	19.2**	3.5**	19.1**	7.6**	8.9**	147.0	66.4	78.0	66.6	65.7	3.0**	8.3**	48.5	9.8**	15.7**
4	Mean (deg)	14.6	67.3	-1.5	48.1	36.1	12.8	13.9	23.4	48.6	50.0	19.1	18.6	24.2	45.6	43.0	87.8	60.9	12.1	52.2	37.0
	SD (deg)	6.0	17.7	2.7	10.0	6.4	7.6	7.0	3.0	16.7	6.7	6.0	7.2	6.8	17.3	12.9	3.9	3.5	6.1	16.8	4.9
	V	35.4	311.6	7.1	100.6	40.4	57.8	49.4	8.9	277.9	45.2	36.4	52.3	45.7	297.8	165.7	15.2	12.0	37.6	281.6	23.9
	CV (%)	41.8	27.8*	214.5	22.5*	16.6**	59.3	47.9	13.0**	37.8*	13.4**	32.7*	40.5	30.4*	44.9	31.0*	4.4**	5.7**	52.6	36.8*	12.7**
5	Mean (deg)	21.1	61.8	79.5	46.1	40.4	6.0	48.3	30.3	49.8	55.2	10.3	62.3	54.9	49.5	50.5	107.1	113.8	-48.3	56.6	57.5
	SD (deg)	3.5	4.9	6.3	3.9	7.6	3.8	6.2	6.3	3.2	5.1	4.6	4.4	4.8	3.1	6.5	2.4	4.4	7.7	4.3	4.7
	V	12.0	23.6	40.1	15.6	57.8	14.5	38.8	40.3	10.3	25.8	21.2	19.7	23.1	9.7	42.8	5.9	19.0	59.6	18.2	22.6
	CV (%)	16.9**	7.9**	7.9**	8.5**	20.0**	60.7	13.1**	21.1*	6.5**	9.2**	46.1	7.1**	8.8**	6.3**	12.7	2.3*	3.8**	15.2**	7.5**	8.18**
6	Mean (deg)	0.8	60.6	102.7	39.3	38.7	22.3	29.0	26.8	45.5	44.1	27.2	35.3	88.9	48.9	52.9	135.2	71.8	-27.7	52.2	49.7
	SD (deg)	2.6	3.4	8.7	5.0	3.5	2.9	4.0	3.5	3.1	3.7	2.5	5.2	6.2	5.1	3.4	37.6	4.7	20.2	6.4	4.6
	V	6.5	11.8	75.4	25.4	12.2	8.2	16.4	12.1	9.8	13.7	6.3	26.9	38.3	25.8	11.6	1412.7	22.5	408.1	41.4	21.3
	CV (%)	356.6	5.6**	8.7**	13.1**	9.3**	12.4**	13.8**	12.6**	7.0**	8.2**	9.1**	14.1**	7.0**	10.6**	6.3**	30.7*	6.6**	83.0	12.6**	9.3**
7	Mean (deg)	22.1	73.8	-6.5	26.7	33.2	-14.2	34.7	11.2	36.3	66.6	2.6	38.0	11.6	35.2	65.9	94.7	88.0	12.8	29.6	36.0
	SD (deg)	9.7	4.6	5.2	6.2	4.6	4.6	5.6	5.8	1.1	3.1	3.4	5.9	4.8	1.4	2.6	4.6	5.0	6.9	3.4	3.7
	V	94.4	20.8	27.5	38.4	20.7	21.3	30.9	33.2	1.2	9.8	11.4	34.3	23.2	1.8	6.6	21.0	25.3	47.5	11.4	14.0
	CV (%)	43.7	6.7**	76.3	22.9*	13.8**	35.1*	15.1**	48.4	3.0**	4.7*	121.2	14.7**	42.0	3.9**	3.9**	4.8**	5.8**	57.3	11.3**	10.4**

ShF: shoulder flexion; ElF: elbow flexion; WrE: wrist extension; RKnF: right knee flexion; LKnF: left knee flexion; *Average variability; **Small variability; not marked CV: high and very high variability.

Table 6: Values of acceleration of "playing hand" in the moment of racquet's contact with the ball—entire group and particular players—means, standard deviations (SD), variations (V), and coefficients of variation (CV).

	Variable	Topspin forehand
Entire group ($n = 7$)	Mean (m/s^2)	149.2
	SD (m/s^2)	8.6
	V	73.7
	CV (%)	5.8**
Players		
1	Mean (m/s^2)	159.4
	SD (m/s^2)	3.1
	V	9.6
	CV (%)	2.0**
2	Mean (m/s^2)	160.1
	SD (m/s^2)	14.3
	V	204.6
	CV (%)	9.2**
3	Mean (m/s^2)	158.9
	SD (m/s^2)	3.6
	V	12.9
	CV (%)	2.3**
4	Mean (m/s^2)	156.0
	SD (m/s^2)	6.8
	V	46.0
	CV (%)	4.3**
5	Mean (m/s^2)	138.4
	SD (m/s^2)	10.1
	V	101.5
	CV (%)	7.3**
6	Mean (m/s^2)	157.9
	SD (m/s^2)	1.8
	V	3.1
	CV (%)	1.1**
7	Mean (m/s^2)	148.3
	SD (m/s^2)	14.3
	V	204.7
	CV (%)	9.6**

*Average variability. **Small variability. Not marked CV: high and very high variability.

4. Conclusions

In this study of the table tennis topspin forehand, the use of an IMU system facilitated measurement of the duration of individual phases and key kinematic parameters, as well as estimation of their variability. The low CV values for duration of most phases (mainly Hitting and Followthrough) for both individual athletes and the entire group indicates small variability in this constant stroke characteristic.

Intraindividual variability of angles was most often low or medium, indicating repeatable technique among the participating players. Nevertheless, it is impossible to state unequivocally that any player repeated the same task with the same movement pattern. As the literature suggests, the large variability in movement may be functional and compensatory in character, reflecting motor adjustment of various parameters.

Inter- and intraindividual variability of joint angles was generally low for the knees and the elbow joint. The greatest observed variability was in extension at the wrist joint, with medium or large variability of the shoulder joint in many cases. It seems likely that the observed changes at the shoulder and wrist joints are mutually dependent (i.e., changes at one joint are compensated for by changes at the other).

There was low variability in hand acceleration. Despite the variability of some angles in subsequent events, it can be concluded that individual players achieved relatively constant hand acceleration at the moment of contact between racket and ball. This indicates compensatory changes in angular parameters at one joint to offset changes at another.

Data Availability

The raw data.xls data used to support the study findings are included in the supplementary information file (available here).

Disclosure

This research was performed as part of the authors' employment at the University School of Physical Education in Wrocław. No other parties were involved in writing, editing, or approving the manuscript, or in the decision to publish.

Conflicts of Interest

The authors have no conflict of interest to declare.

Supplementary Materials

Table S1. *(Supplementary Materials)*

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