IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 1 June 2023, accepted 25 June 2023, date of publication 28 June 2023, date of current version 28 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3290471

RESEARCH ARTICLE

Objective Evaluation of Coordinative Abilities and Training Effectiveness in Sports Scenarios: An Automated Measurement Protocol

CHIARA CARISSIMO[1], (Graduate Student Member, IEEE),
GIANNI CERRO[2], (Member, IEEE),
TOMMASO DI LIBERO[3], (Graduate Student Member, IEEE),
LUIGI FERRIGNO[1], (Senior Member, IEEE),
ALESSANDRO MARINO[1], (Senior Member, IEEE), AND ANGELO RODIO[3]

[1]Department of Electrical and Information Engineering "Maurizio Scarano," University of Cassino and Southern Lazio, 03043 Cassino, Italy
[2]Department of Medicine and Health Sciences "Vincenzo Tiberio," University of Molise, 86100 Campobasso, Italy
[3]Department of Human, Social and Health Sciences, University of Cassino and Southern Lazio, 03043 Cassino, Italy

Corresponding author: Chiara Carissimo (chiara.carissimo@unicas.it)

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by BIO-MED of the IRB SUSS of the University of Cassino and Southern Lazio.

ABSTRACT The monitoring of coordinative abilities in sports applications is often carried out by trainers that adopt subjective protocols and evaluations not supported by repeatable and reproducible measurement setups. This often leads to unreliable evaluations that do not allow us to quantify the positive or negative effect of some training in a simple way. In this scenario, the rapid spreading of wearable devices able to capture human movements providing data to the users could be a useful instrument to face the problem of simplifying the development of automated, repeatable, and reproducible measurement procedures easily adoptable by a community of athletes or coaches. Following this path, the paper proposes an automatic measurement protocol for the assessment of coordinative abilities based on the use of IMUs embedded in wearable devices. A new protocol based on the ruler and tapping tests and a set of objective key performance indicators, derived from IMU measurements, to evaluate the outcome of the test is then developed. In detail, the protocol is based on the sequence 1) ruler test; 2) tapping test; 3) ruler test. The tapping test is performed until energy exhaustion to try and identify, from inertial data, features that can describe possible fatigue effects and correlations with reaction time. Ruler tests are adopted to evaluate the reaction time. The first ruler test provides reaction time information in rest conditions, while the last one considers it after a repeated movement. The comparison of these two times will show whether the reaction time changes after a fatigue condition. An algorithm capable of calculating the number of tapping and the reaction time of each subject is implemented to evaluate the accelerometric data acquired during the tests. Therefore, the impact of the work is two-fold: from an engineering point of view, the automation and performance evaluation of the proposed algorithm is provided; from a sport-medical perspective, the main finding is a general reduction of the reaction time after the energy-exhausting tapping test, as if this last could be considered as a powerful warm-up exercise for sports people. Two are the main results achieved: i) the proposed protocol allows a reduction of the reactions time in about the 83% of cases; ii) the proposed measurement system allows obtaining, regarding the tapping test, additional very useful quantities as the tap intertemps, frequency spectra, and acceleration excursions, which typically are not provided in state-of-the-art tapping test execution.

INDEX TERMS Tapping test, IMU sensors, reaction time, viscoelasticity, measurement protocol.

The associate editor coordinating the review of this manuscript and approving it for publication was Gang Wang.

I. INTRODUCTION

Coordinative abilities are neuro-motor characteristics that distinguish our movements [1], which influence the learning and refinement of new motor acts and their stability over time. Coordination allows people to perform a movement, or group of movements, with better quality and effect [2]. Furthermore, these abilities promote the efficient execution of motor actions under a variety of conditions, enhance the restructuring of movements in high-performance training phases, improve basic and applied motor abilities, and aid the use of conditional abilities [3]. Indeed, they are the basis for learning and improvement of technical abilities and are in close cooperation with conditional abilities [4]. Body movement is determined by the individual's ability to effectively use the surrounding environment information [5] and coordinative training interventions can be fundamental in enhancing also cognitive abilities, on which functional motions deeply depend [4]. The most common assessment of neurological efficiency is reaction time [6], [7]. Reaction time is the period between the onset of stimuli and the initiation of reactions to them. This factor is a valuable indication for investigating central nervous system ability and motor function [8]. Recent work states that maintaining a good state of reaction time training can help us to improve our ability to concentrate and overall performance [9]. Body training is a fundamental practice, but training coordinative capabilities are equally important, and rarely it is considered a specific training program. Authors in [10], reported that subjects with better visual information acquisition abilities perform better. For instance, an athlete with a trained visual system performs better in comparison with an athlete of similar characteristics, but with a less performing visual system. To evaluate reaction time, a possible methodology concerns oculo-manual examinations, such as the Ruler Test (RT) and Tapping Test (TT). These tests are often used as an indicator for visual control, hand-eye coordination, and response time [6], [8]. To date, the handling of these tests is generally carried out by an operator.

For instance, in the case of RT, the operator held the ruler in the air aligning the zero point with the subject's index finger and thumb fingertips. Without notice, the operator dropped the ruler and the subject should catch the ruler as fast as possible. The distance traveled by the ruler before catching is measured in centimeters and transformed in reaction time by the standard formula [11]. As concerns tapping tests, the operator counts the number of taps performed in a timeframe, either by adopting a specific app or by visual counting. In both the described cases, the evaluations may be affected by a subjective component related to the presence of the operator, which would make the results inaccurate. These boundaries can be overcome by the use of objective measurement systems that can reduce evaluation biases and make testing automated [12]. Furthermore, although the above-mentioned limitations can be overcome by the automation and objective evaluation of the measurements during both RT and TT, such tests are still adopted singularly only for assessing the current status of the involved sportsperson. It is anyway possible to combine them in a specific sequence. Particularly, the RT is usually adopted to assess reaction time and, therefore, it can be seen as a cognitive readiness index. The TT, on the other hand, contributes to training the coordinative abilities and focusing on a specific repetitive action. Accordingly, the execution of TT could affect the readiness level, which changes in relation to external stimuli. To assess it, a procedure employing the sequence RT-TT-RT is experienced to evaluate such an effect. Starting from such considerations, the present work's contributions are mainly devoted to: i) propose a measurement protocol to have both training and evaluation purposes for sports people, capable to produce a detailed and easy-to-read report on their physical status; ii) create an automated measurement set-up, which is able to capture movements through the use of an Inertial Measurement Unit (IMU) and process the acquired data in real-time to estimate several quantities of interest related to previously described purposes. Even if the use of optical systems which capture human movement, such as cameras, surely warrant high accuracy, according to [13] and [14], an IMU wearable device has been considered in the paper since it is well suited for performing home-environment monitoring of motion tracking reducing costs and infrastructure needs. In fact, when a camera-based measurement system is considered, to obtain very accurate results, it is advisable to have high-resolution cameras, which entails higher costs with respect to inertial sensors. Moreover, a motion test using cameras requires a suitable workspace and a specialized staff to set up the system. On the other hand, in addition to being low-cost and easy-to-use devices, inertial sensors allow motion analysis to be carried out even in everyday environments. In fact, wearable devices are non-invasive monitoring instruments that can easily be integrated into a smartwatch or ring. The slightly lower accuracy of inertial wearable devices versus high-speed cameras is widely recovered by their flexibility, portability, low cost, ease to wear, and no need to have a structured environment where to perform the test.

In the developed set-up, the adopted IMU has been placed on the ruler, for the homonym test, and on one finger of the dominant hand of the participant for the tapping test. The acquisition of raw data from the sensor is managed by automated software working on a laptop, wirelessly connected to the sensor itself. In addition, we adopted an algorithm able to detect taps and compute inter-tap times (intertemps), previously validated in [12], where different methodologies to measure tapping features were compared and assessed in terms of results compatibility. The test evaluation is carried out by adopting synthetic figures of merit. The advantage of having an automated system from data acquisition to data processing makes it possible to reduce uncontrollable influence components such as observer evaluations that could be affected by a percentage of subjectivity that would affect the reliability of the results.

This project was approved by the Institutional Review Board of the University of Cassino and Southern Lazio (No. 24777.2022.12.12). Before participating in the study, subjects have been informed in detail about the protocol. The content of the present work is structured in sections as follows. Section II explains the State of the art about usage of objective measurement tools in the sports environment and the description of the coordinative tests. In Section III information about the developed set-up, the measurement protocol, and the data processing cycle is given. Results are reported in Section IV and their discussion is provided in Section V. Section VI concludes the paper with final remarks and discusses future applications of the proposed protocol.

II. STATE OF THE ART

In the last decade, a good amount of research articles have been focused on the collection of data regarding the benefits of physical training. As an example, in [15], it has been proved that physical training in a variety of sports improves certain abilities such as agility and coordination. Such aspects are crucial for all physical activities, particularly athletic performance, indeed, in the scientific literature, there were many reports of eye-hand coordination training that enhanced an individual's motor performance [10].

In the category of eye-hand coordination papers, particularly relevant is [16], where six weeks of upper extremity proprioception training were employed as an intervention to enhance table tennis players' reaction time. Participants demonstrated improved eye-hand coordination and response speed. Using the ruler drop test, each player's response time was assessed. The control group received only conventional training, whereas the experimental group received conventional training together with proprioception instructions for six weeks. After such a time interval, the athletes' response times were once again assessed. The research showed that the reaction time was shorter for the experimental group than for the control group.

In [15], the RT was used to assess subjects' attentiveness and agility. The research indicates that four weeks of conventional archery instruction may enhance the eye-hand coordination of inactive young men. However, to increase the impact of training on the response time of the upper extremities, extra training or intervention may need.

According to research on gender differences in reaction time, men and women respond differently to a number of stimuli [17]. Particularly, in Wadoo et al. research [18], the authors examined the effects of gender and physical activity on adults' visual and auditory response times: it was found that there is a substantial difference between women's and men's reaction times. Another study also examined the impact of a 9-week educational intervention on the response time of 15 to 18-year-old adolescents and discovered that both girls' and boys' reaction times improved after the training [9].

In some studies, the assessment of coordination abilities is carried out through the introduction of specific technologies, as in the work [19], where the authors aimed to create a simple response time measurement device. The technology must compute the speed of human responses based on cognitive and motor factors. Several steps of product development were carried out, including the discovery of user needs, idea development, embodiment design, building, and testing. In particular, the adopted idea was to use a light stimulus to assess response time, taking into account differences in light hue, flash rate, and intensity. A series of tests showed that these features might be used to evaluate and differentiate response time, taking cognitive and motor time into consideration. It was also shown that the device can tell the difference between normal response times and those of tired people. In Grigoroiu et al. [20], the authors attempted to investigate the reaction time to complex visual stimuli for the upper limbs in 18–20-year-old students. Using two computerized tests, the features of the individuals' upper limbs were determined: the complex response time of the dominant hand and the non-dominant hand. The data were analyzed using the TReactionCo software, which enabled the recording and storing of response times for each execution as well as the display of the arithmetic mean, highest value, and lowest value for a series of determinations. In assessments of complex reaction times for both the dominant and non-dominant hand, the results demonstrated a statistically significant difference between male and female responders.

Coordination exercises such as tapping are used in clinical settings to assess motion-related pathologies. In [21] authors suggested the bradykinesia incoordination (BRAIN) test to evaluate Parkinson's disease (PD) patients' movements. The BRAIN test is a validated keyboard tapping test used to assess the distal motor function of PD patients remotely. The test was able to identify tiny changes in the fluctuation states of the motor system that were not clearly reflected in the secondary scores of the MDS-UPDRS-III [22] that were utilized throughout the research. In research by Van Schooten et al. [23], the authors intend to investigate the psychometric features of ReacStick measures of reaction time and executive functioning in healthy older individuals living in the community. An unavoidable time constraint may result in information that complements the standard metrics. The ReacStick is a good way to test an older person's response time, and it could be used to figure out how likely they are to fall.

In this field, the objective assessment of physical tests is rapidly moving towards the employment of wearable technology-based devices [24]. They are able to recognize gestures by detecting limb motions in space and time, which was a crucial characteristic for collecting data on users [25]. Out of the different devices used to detect human motion, IMUs are the most widely used because they are small, networked, cheap, and easy to use. Inertial data provide information on acceleration, angular velocity, and magnetic field change. Due to these characteristics, IMU sensors may be used in several fields, including sports and medicine. The use of inertial sensors in the sporting field, therefore, represents a valuable tool that can provide objective information that,

TABLE 1. Mean and standard deviation of the anthropometric data of all subjects.

Information	Mean (μ)	Std. Dev. (σ)
BMI $[kg/m^2]$	23.31	3.63
Finger Length $[cm]$	8.69	0.89
Age $[y]$	25.33	3.71

in addition to standardized tests, allows for more robust and accurate results.

III. MATERIALS AND METHODS

A. THE MEASUREMENT PROTOCOL

In this study, eighteen voluntary students from the University of Cassino and Southern Lazio are involved. In particular, 9 males and 9 females took the test during an internship activity in the framework of the Motor Science Course. For each subject, anthropometric data that are age, length of the index finger used for the tapping test, weight, and height are collected. More in detail, height and weight are combined in a synthetic parameter that is the Body Mass Weight (BMI). Fig. 1 describes anthropometric information for each subject, while in Tab. 1, the mean and standard deviation of the main information of the group are reported. For a complete overview, information on sports and personal activities has been requested and summarized in Tab. 2. Participants are informed about the structure of the protocol and the execution of the tests. In detail, they are asked to perform a test containing three different exercises in the following order: ruler test; tapping test; ruler test. The first exercise with the ruler shows the reaction time at rest, then they are asked to perform the tapping test in an energy-exhausting fashion, and, finally, the ruler test is repeated again to highlight any possible change in the reaction time after the tapping test task. To record the inertial data of the different tests, the sensor is fixed by the operator on the ruler for the RT and the index finger of the dominant hand for the TT; Fig. 2 shows the position and orientation of the sensor in the three different phases described above. Data acquisition starts at the beginning of the test and stops after the last ruler test. At the end of each test, the data are saved in the cloud via the proprietary app. This project was approved by the Institutional Review Board of the University of Cassino and Southern Lazio (No. 24777.2022.12.12). Before participating in the study, subjects have been informed in detail about the protocol. Moreover, informed consent and authorization about benefits and risks have been obtained in accordance with the Declaration of Helsinki for Human Research of 1964.

B. THE DEVELOPED SET-UP

To perform objective measurements an IMU sensor is selected. In particular, the chosen device is a MetaMotionR (MMR) and it is made by MBIENTLAB company [26]. It is equipped with the following triaxial sensors: accelerometer, gyroscope, and magnetometer. Furthermore, thanks

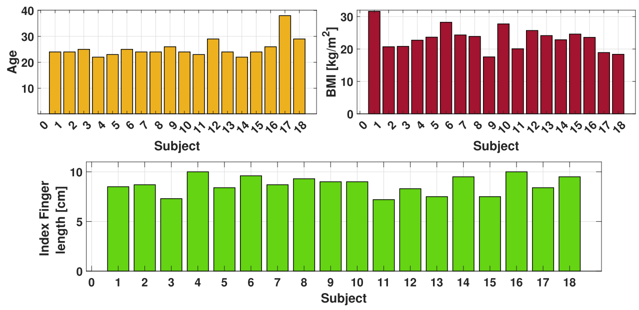


FIGURE 1. Anthropometric data evaluated for each subject.

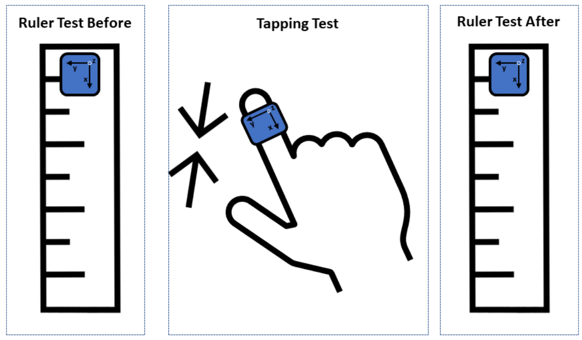


FIGURE 2. Measurement protocol: the IMU sensor orientation and positioning during the three exercises.

TABLE 2. Sports and activities done in free time by each subject.

Activity	Subject IDs
None	ID1; ID17
Play Guitar	ID2;ID10;ID16
Gym	ID3; ID4; ID7;ID10;ID14
Videogames	ID4;ID5;ID6;ID8;ID16
Basket	ID5
Padel	ID6;ID8;ID13
Tennis	ID8
Dance	ID9;ID14;ID15
Body Building	ID10
Taekwondo	ID11
Weightlifting	ID12;ID13
Swimming	ID14
Athletics	ID14
Football	ID16
Fitness	ID18

to MEMS (Micro-electromechanical systems) technology, it can be used as a wearable system. The device dimensions (including the case) are: L: 36 mm × W: 27 mm × H: 10 mm and its weight is about 8.5 grams. The setup reported in Fig. 3 has been adopted both for ruler and tapping tests, according to the measurement protocol explained in subsection III-A. Pictures of the set-up arranged for each test can be seen in Fig. 4. In detail, in Fig. 4a, two people are involved to perform the ruler test. The first one keeps the ruler and, at a random instant, leaves it falling, while the second person should catch it in the fastest possible time as soon as the ruler is left in falling mode. Fig. 4b reports another voluntary person performing the tapping test. In this case, the only constraint is

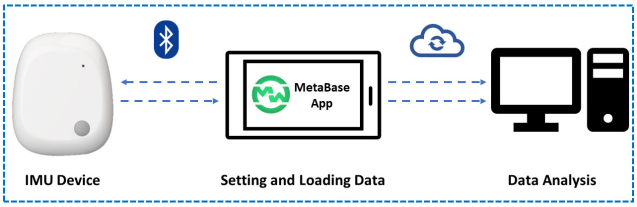
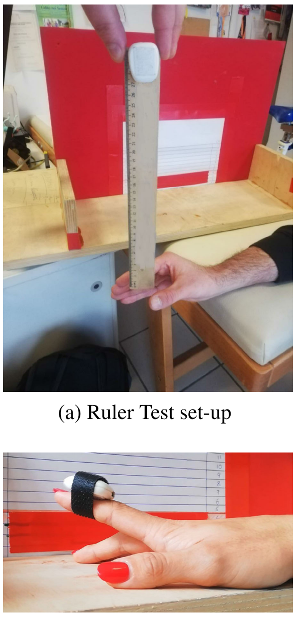


FIGURE 3. The implemented setup is characterized by sensor, devices, and technology used in the acquisition data process.



(a) Ruler Test set-up

(b) Tapping Test set-up

FIGURE 4. Pictures of the set-up mounted for executing ruler and tapping tests.

represented by the tapping amplitude that must be as close as possible to the one indicated in the handcrafted background panel, equal to 4 cm.

The operations of setting sensor parameters and uploading data are carried out via Metabase's proprietary application [27], and the MMR communication technology is based on the Bluetooth Low Energy 4.0 Smart$^{\delta}$ module.

Acceleration data are acquired via the MMR by setting a sampling rate of 100 Hz and a range of $\pm 8g$, where g is the gravity acceleration constant, equal to 9.81 m/s^2. The overall test duration is not fixed because it depends on the subject's endurance time during the TT. Once the data has been acquired, it is stored in a cloud and then downloaded to a PC for analysis. It is worth noting that the setup is composed of three elements: the IMU sensor, a gateway device, and a PC. In order to minimize the hardware impact, the setup could also be composed of the sensor and the PC only. Nevertheless, for flexibility reasons and to fast execute the tests, a tablet has been used as a gateway in order to exploit Bluetooth low-distance ranges, without the need to have the processing unit close to the test location.

TABLE 3. Validation of proposed algorithm with respect to golden standard methods.

RULER TEST	Mean Value	Std.Dev.	Overlapped pdf Area
Manual Inspection	0.170	0.029	0.87
Our Algorithm	0.160	0.031	
TAPPING TEST (10 s)	**Mean Value**	**Std.Dev.**	**Overlapped pdf Area**
Application	61.4	6.5	0.93
Our Algorithm	62.3	5.9	

C. AUTOMATED MEASUREMENT ALGORITHM

To analyze the data set, an algorithm (see Fig.5), that receives the raw accelerometer data of the single test as input and computes the corresponding time intervals of RT and TT activities is implemented.

The algorithm acquires all raw acceleration data along three axes and separates those belonging to Ruler Tests from data deriving from the execution of the Tapping Test.

An example of accelerometer data recorded during a test is shown in Fig. 6. In detail, the shown data consist of a demo test, lasting 8 s, where the sequence RT-TT-RT is reported. A small amount of data between RT and TT is discarded since it refers to the sensor position change from the ruler to the subject's index finger.

The main operations of the developed algorithms concern the estimation of reaction time from the ruler test data, by analyzing the accelerometer data along the x-axis (Fig. 5a) and the computation of the number of taps by considering the accelerometer data along the z-axis (Fig. 5b). The axis selection is made by considering the sensor orientation and the main direction of motion, i.e. the one in which a greater excursion of acceleration is observed.

Going into deep with the developed algorithm, the main sections are explained in the following. For the RT algorithm, the Matlab™ routine *findchangepts* [28] is used to detect the acceleration abrupt change during the falling ruler, while for the tap number detection, the *findpeaks* [29] routine is chosen. The adopted algorithm has been already validated in our previous work [12], at least as concerns the estimation of reaction time and number of taps. Furthermore, in [12], results derived from the IMU sensor were also compared with standard visual inspection and with those provided by a Tablet app that used its display as a touch sensor. Particularly, Tab 4 in [12] shows the obtained results that confirm full compatibility with a confidence level of 95%.

Briefly, the characterization results are reported in Fig. 7, in terms of Gaussian probability density functions (pdf), obtained thanks to the Central Limit Theorem (n = 400) where a high-level of overlapping is visible, and in Tab. 3, in terms of Mean Value and Standard Deviation (Std.Dev.). Such an overlapping has been quantified in terms of common area in Tab. 3 as "Overlapped pdf Area" column values [12]. The obtained high level of agreement allows using the automated algorithm instead of manual inspection and, therefore, by adopting an objective procedure, and increasing the overall reliability of the obtained results, especially in terms of

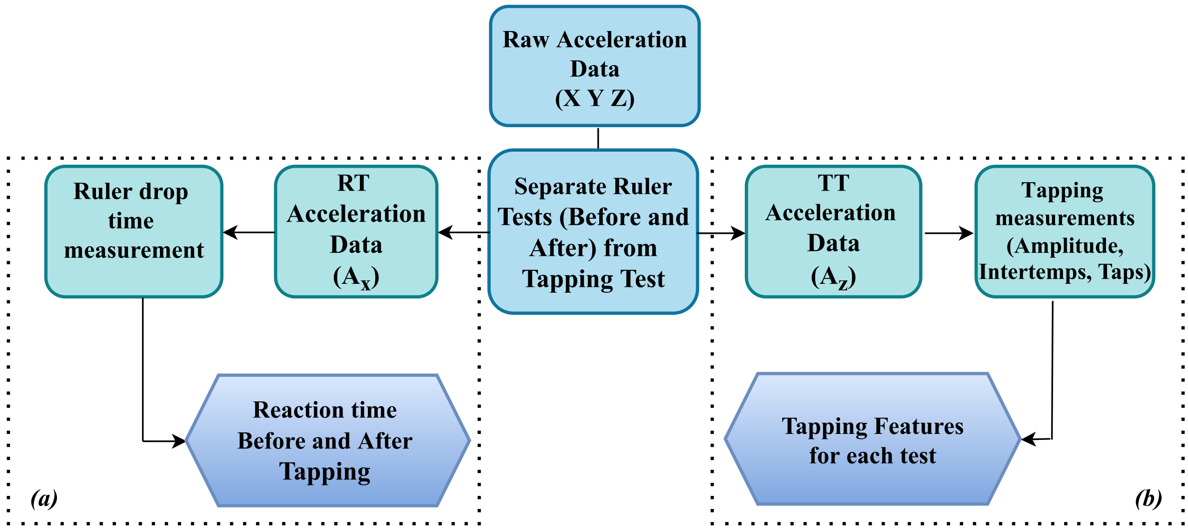


FIGURE 5. **Automated measurement algorithm Age.eps diagram: in part (a) the procedure to compute reaction time, while in part (b) the process used to obtain the number of tapping are reported.**

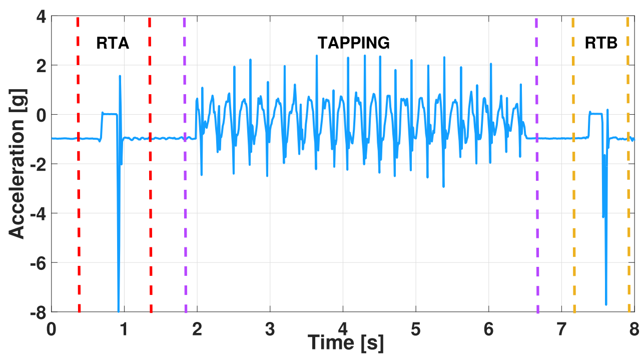


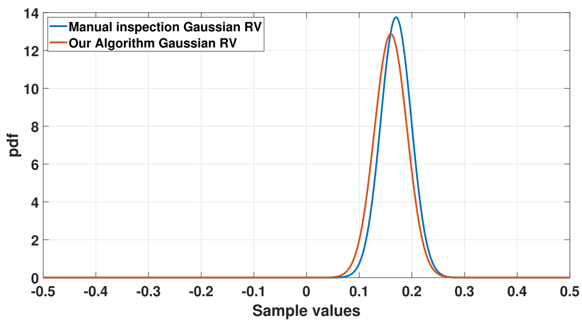
FIGURE 6. **Example of the accelerometric data along the x-axis recorded during a complete test.**

processing speed and avoidance of systematic errors, that could occur when human operators are involved. Clearly, the comparison has been carried out in a very controlled environment, where all possible systematic errors by the operators have been fixed.

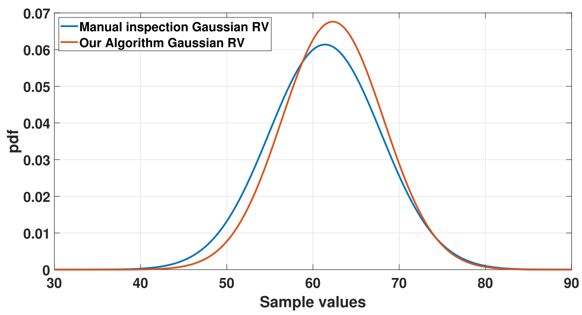
In its full version, the algorithm performs a deeper analysis with particular reference to TT.

In detail, the accelerometer data are used to:

- count the total number of taps of the executed test and grouping them in variable time observation windows;
- compute the intertemps, i.e. the time distance between each couple of consecutive taps to highlight possible fatigue phenomena that could arise in the subject;
- estimate the frequency behavior in total size (whole test duration), batch size (for specific observation window) of the accelerometer data.
- compute the acceleration excursions: the amplitude of the acceleration data is calculated and monitored during the whole test execution time.



(a) Ruler Test distributions



(b) Tapping Test distributions

FIGURE 7. **Distribution of ruler and tapping values for validation purpose.**

IV. RESULTS

In this section, detailed results obtained through the implemented algorithm are shown for the ruler and tapping tests. Particularly, from the ruler test, pieces of evidence about reaction time subject by subject and comparison between obtained times before and after exhausting tapping task are provided. As the tapping test regards, several processing aspects are considered, and, particularly, results are grouped

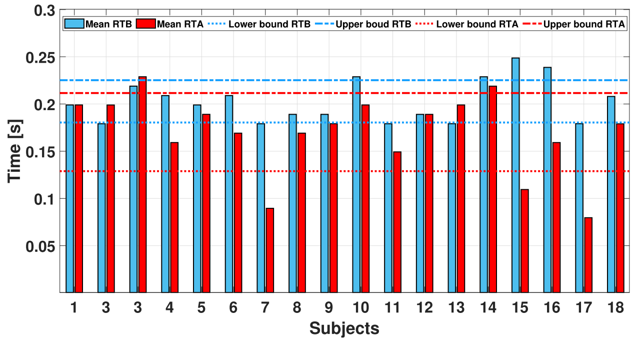


FIGURE 8. Bar Diagram of reaction times before and after tapping test evaluated for each subject.

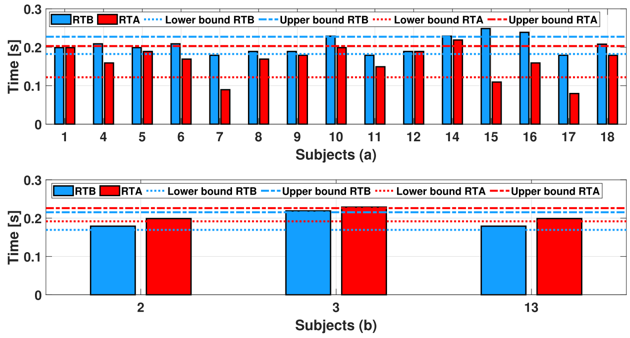


FIGURE 9. Bar chart of reaction times before and after the tapping test for subjects with improved (a) and worsening (b) RTA.

as follows: 1) Tap counting and grouping; 2) Intertemp evaluation; 3) Frequency behavior observation; 4) Acceleration Amplitude Excursions. The provided results can easily be accessed by a user through a simple selection in the developed algorithm interface. Particularly, they can be evaluated by a medical doctor to achieve a personalized report about the subject's health status and coordinative capabilities.

A. REACTION TIME EVALUATION

The proposed test has been used to evaluate the reaction time in a group of healthy subjects. In particular, RT is used to evaluate and compare the reaction time before (RTB) and after (RTA) the tapping test. A bar diagram in Fig. 8 shows the obtained results.

The horizontal lines indicate RTB and RTA bounds for all subjects. A bound is defined as the following interval: [Lower Bound, Upper Bound] = $[\mu - \sigma, \mu + \sigma]$, where μ and σ are the average and the standard deviation values computed on the whole subject sample. The red lines define the RTA bound while light blue lines include the RTB bound. All participants' reaction times fall into the bound in the case of RTB, i.e. before carrying out the tapping test. On the contrary, the RTA, i.e. the reaction time evaluated after the tapping test, has subject-based specific behavior, not always adhering to the computed bound.

To better analyze the results, the subjects are divided into two groups: subjects with RTA $\leq$ RTB and subjects with RTA $>$ RTB. In Fig. 9 (a), it can be seen that 15 out of 18 subjects do not increase their reaction time, while the remaining 3 have a slight worsening of it after the tapping exercise, as can be seen in Fig. 9 (b). All summary values of mean and standard deviation calculated for the three groups identified for the reaction time tests are given in Tab. 4. Due to the inherent nature of the procedure, a single value of RTA and RTB is available for each subject. Therefore, a detailed analysis of the single-subject effect cannot be performed. Anyway, it is possible to consider the whole group as a representative sample of a population, being identified by young and healthy people. In this approach, results provide an average decrease in the reaction time after the TT, although the range intervals are partially overlapped. The idea

TABLE 4. Mean and standard deviation of reaction times calculated for each subgroup.

	RTB Mean (μ) [s]	RTB Std.Dev. (σ) [s]	RTA Mean (μ) [s]	RTA Std.Dev.(σ) [s]
All Subjects	0.200	0.022	0.178	0.033
Subjects with RTA<RTB	0.204	0.023	0.169	0.031
Subjects with RTA>RTB	0.192	0.023	0.209	0.017

to repeat the process multiple times on the same subject has an important drawback: it is not possible to ensure the same measurement conditions needed to evaluate features such as repeatability and type-A uncertainty contributions. Moreover, to assess the statistical significance of results, three statistical analyses, such as the Friedman test [30] and the Durbin-Conover test (pairwise comparisons) [31], and also the Paired Samples T-Test [32] have been carried out. For each of them, the obtained P-values were evaluated and compared with the typical reference level of 0.05. As for the Friedman test, a P-value equal to 0.018 was obtained. As for the Durbin-Conover test (pairwise comparisons), the P-value was equal to 0.014. As for the Paired Samples T-Test, considering the Hypothesis that the measures (RTA and RTB) have a non-null difference mean value, a P-value of 0.006 resulted. Therefore, with a confidence level higher than 95%, it is possible to state that there is a statistically significant meaning between reaction times before and after the tapping test.

B. TAPPING TEST RESULTS

The tapping exercise is performed between the two ruler tests and the subject performs it until he/she is exhausted. From the raw data of this test, thanks to the validated algorithm, several aggregated and individual features, which provide more detail of the subject's performance, can be extracted.

1) TAP COUNTING AND GROUPING

To evaluate the performance of the tapping test, the first observation concerns the number of taps performed during the whole test. As can be seen in Fig. 10 the upper graph shows the total taps obtained for each subject, and the other plot shows the total time taken to perform the test.

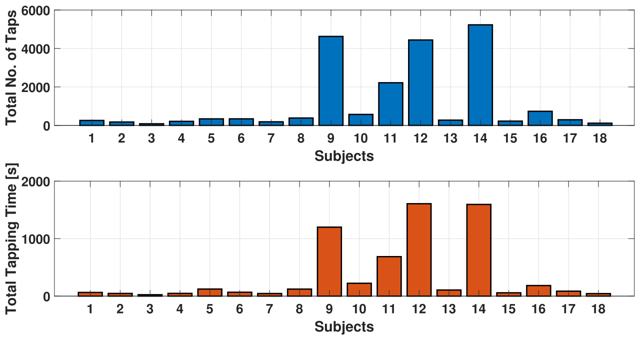


FIGURE 10. Bar diagrams: the first row shows the Number of Tapping for each subject; the second row displays the total tapping test time for each subject.

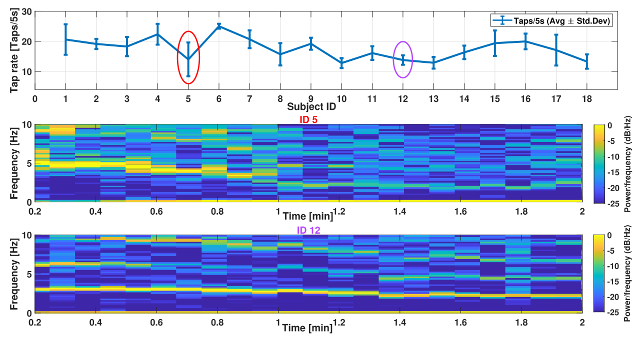


FIGURE 11. Error bar in Tapping Tests: evaluation of mean value (Avg) and standard deviation (Std.Dev) for all involved participants. Spectrograms related to IDs 5 and 12, concerning the first 2 minutes of activities, are reported in subplots.

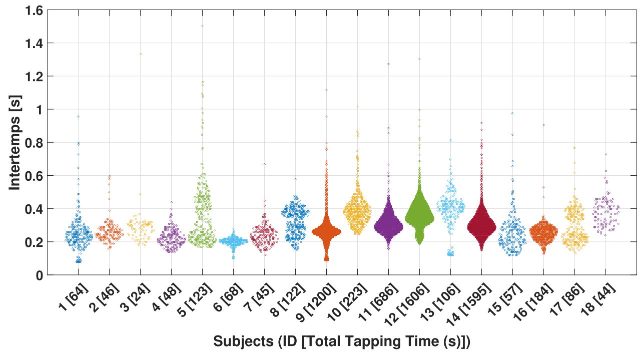


FIGURE 12. Intertemps distribution for each subject during the whole tapping test.

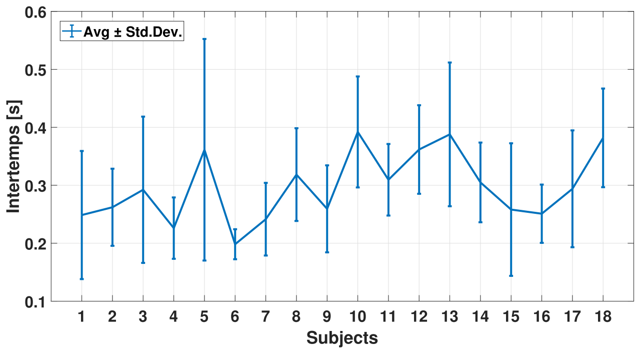


FIGURE 13. Mean (Avg) and Standard deviation (Std.Dev) of intertemps computed for each subject during the tapping test.

From the results, it can be seen that 4 out of 18 participants showed a higher degree of resistance during the exercise, managing to perform the test for more than 20 minutes and scoring more than 4000 taps. On the other hand, 7 subjects were able to perform the exercise for more than one minute, while the remaining 7 performed the test for less than one minute. The variability of the time taken to perform the tapping test until exhaustion strongly depends on the physiological characteristics of each subject.

Fig.11 shows the error bar in the TT. In the first subplot, it can be seen the mean value and the standard deviation of the number of taps computed every 5 seconds for each participant. It can be observed a non-uniform behavior among participants: specifically, their variability is quantified by the standard deviation reported as a vertical bar in the plot. To better illustrate this phenomenon, two limit cases have been considered: ID 5 and ID 12. The TT evolution of the specified participants has been computed by spectrogram function and reported in the second and third subplots, respectively. To make a uniform comparison, only the first 120 s of tests have been reported for both IDs, as well as the spectrogram settings have been taken in coherence with the error bar computation settings (5-second-window, no overlap). The yellow lines in the spectrograms indicate the frequencies containing the highest power density. As ID 5 concerns, their high standard deviation value results in a highly variable main frequency behavior (i.e. the yellow line often changes its frequency position). On the contrary, observing ID 12's test trend, a main frequency equal to 3 Hz is constantly kept along the test's duration, justifying the lower standard deviation value.

2) INTERTEMP EVALUATION

A further processing stage consisted of the assessment of the intertemps, i.e. the time distance between two consecutive taps. In detail, the intertemp time distribution for each subject during the whole test is shown in Fig 12. Subjects who performed a long test (IDs: 9, 11, 12, and 14) obtained most intertemps in [0.3, 0.4] s range, while for subjects performing a shorter tapping test, the overall intertemp distribution generally moves downward, proving a faster way to tap, which leads to a shorter endurance time. (Fig. 13).

To obtain quantitative overall information about their distribution, the mean and standard deviation have been calculated for each subject. Obtained results are presented in the form of error bars superimposed on the mean values and they are shown in Fig. 13.

The results clearly state that the mean values are only an approximation of the real behavior, since the standard deviation values are generally very high, especially for subjects performing a short tapping test, while they got a

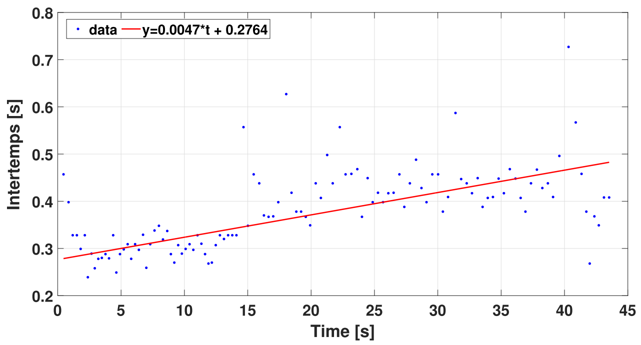


FIGURE 14. Example of linear fitting for intertemps versus task execution time - Subject ID: 18.

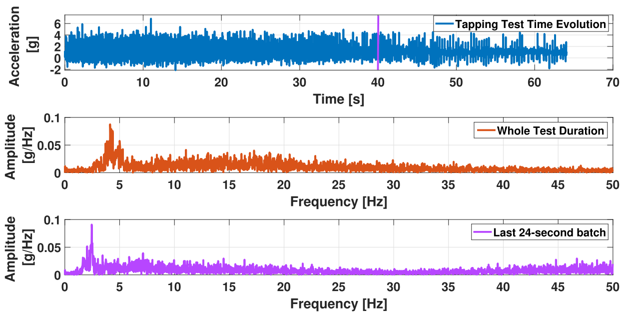


FIGURE 15. Time and frequency behavior observation - Subject ID: 1. Particularly, the frequency spectrum is reported for the whole test duration and considering only the last 24-second interval (batch mode).

TABLE 5. Mean and standard deviation of angular coefficients calculated for all subjects and their different behaviors - intertemp case.

	Mean (μ) [ms/s]	Std.Dev. (σ) [ms/s]
All Subjects	1.70	1.75
Subjects with increasing intertemps	2.38	1.60
Subjects with decreasing intertemps	−0.07	0.06

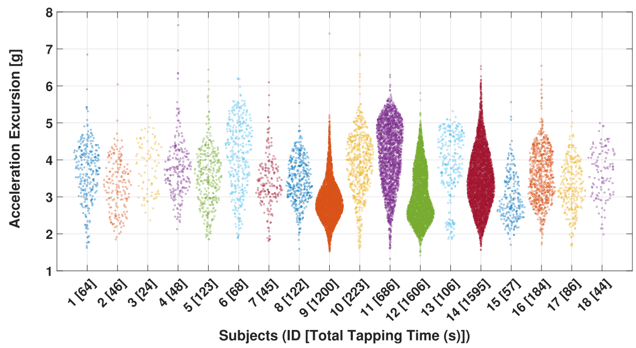


FIGURE 16. Acceleration amplitude distribution for each subject during the whole tapping test.

more stable behavior for subjects having a long-lasting test, as 9, 12 and 14.

To find a possible linear relation between intertemps and test duration, a fitting procedure has been carried out. Results are presented in a graphic mode for Subject 18 (see Fig. 14) and in terms of the mean and standard deviation of the obtained angular coefficients in tabular form (see Tab. 5). In detail, table contents are expressed using ms/s measurement unit, just to obtain higher values easier to be reported and commented. By analyzing such results, it is evident that the majority of subjects show an increase in tap intertemps, which could be seen as a fatigue effect due to prolonged exercise.

In more detail, the obtained results show two different behaviors: i) subjects increasing the time between consecutive taps; ii) subjects keeping a nearly constant rhythm during the test (the decrease rate is almost null). The subjects with an increase in the number of taps were 13, while the remaining 5 were those who showed no substantial change.

3) FREQUENCY BEHAVIOR OBSERVATION

Another way to analyze the timing during the tapping exercise is the observation of the frequency behavior. Particularly, we have at least two ways to analyze frequency data: i) perform a Fast Fourier Transform (FFT) on the whole time sequence data or ii) consider a specific time frame to observe and use it as input for the frequency transformation.

A snapshot of the frequency analysis performed by the algorithm is depicted in Fig. 15. The considered processing ways can be seen in the second and third subplots of the cited figure. It is important to note that the frequency spectra are obtained after a detrend operation, in order to remove the DC component and be able to discriminate frequency components higher than 0 Hz. Although the results are plotted only for Subject ID 1, similar considerations can be drawn for the whole population sample. In detail, the spectrum considering the entire tapping test time series shows a predominant frequency tone at around 4 Hz, with smaller amplitudes in the surrounding frequency interval. On the contrary, when only a batch is considered (the last 24-second case is reported in Fig. 15) a general decrease of the predominant tone frequency location is observed, probably due to a progressive slowing of the tapping rate, still imputable to the fatigue effect the subject experiences.

4) ACCELERATION AMPLITUDE EXCURSIONS

The last proposed processing stage regarding the tapping test is the analysis of the amplitude of the acceleration signals. Indeed, although the subjects were required to get a fixed-angle excursion during the test, the way they got it was not uniform and generalizable. For this reason, after analyzing the time and frequency behaviors, we put our attention also to amplitude values. Symmetrically, we performed the same processing stages as the intertemp case, so it is possible to note their distributions (see Fig. 16) and the linear fitting versus time. In Tab. 6, information about the angular coefficients of the fitted lines is reported.

TABLE 6. Mean and standard deviation of angular coefficients calculated for all subjects and their different behaviors - amplitude excursion case.

	Mean (μ) [mm/s^3]	Std.Dev. (σ) [mm/s^3]
All Subjects	-64	73
Subjects with increasing amplitudes	11	10
Subjects with decreasing amplitudes	-86	69

To get the same information level, we should consider that the fatigue effect in this case should correspond to a decrease in the amplitude values and, consequently, to a negative angular coefficient in the fitting process. That is the case of 14 subjects over 18. It is important to highlight that most subjects exhibit a reduction of the reaction time together with an increase of the intertemp trend and a decrease of the amplitude behavior versus time. This could be a joint phenomenon to be considered as a whole for a medical doctor to assess a subject's performance level.

V. DISCUSSION

In several cases, the literature demonstrates that reaction time might provide an indicator of the central nervous system's ability to receive and synchronize movement conveyed by the peripheral nervous system [33]. This cognitive-motor relationship is essential for several areas of everyday life. In this investigation, we utilized the TT to determine the fatigue index resulting from repeated movements, of eighteen young and healthy subjects. The participants were required to complete the test in an exhaustion modality. Indeed, subjects were instructed to execute the tapping task at the highest pace they could sustain. In addition, we determined that each tap must accomplish a minimum excursion of four centimeters. To ensure that the imposed amplitude was maintained consistently, the minimum amplitude to be maintained was indicated through a red line. A purpose-built box was made to conduct the tests. Furthermore, utilizing RT allowed for the completion of further evaluations in order to have a better understanding of the effects that repetitive motion has on the anatomic body districts and motor tasks. As a matter of protocol, subjects performed an RT before (RTB) and after (RTA) the TT.

The measurements and results obtained during the TT could lead to the definition of a fatigue coefficient. In particular, the increasing intertemps and decreasing amplitude, discussed in the previous section, can be an indication of fatigue occurring during a repetitive exercise performed at maximum speed.

However, when the TT is done at a maximal pace, the frequency lowers in a matter of seconds, indicating the onset of muscular exhaustion. Fatigue could be task-dependent, as are the factors that lead to decreased motor performance during quick and repeated activities [34]. Even though the length of effort is equal, it is feasible to hypothesize that the physiological processes behind fatigue induced by rapid and repeated finger tapping differ from those behind fatigue induced by an isometric contraction [35]. On the other hand, some subjects maintained a fairly constant rhythm while performing the test: in the case of isometric muscular contractions, these processes have been widely explored; they involve changes in excitability in both the spinal cord and M1 networks [36]. During rhythmic motions performed at maximal speed, peripheral exhaustion in muscle fibers and neuromuscular synapses reduces the effectiveness of muscle contractions [37]. Nonetheless, alterations in the excitability of spinal and supraspinal regions also define fatigue in these motions [36]. At the cerebral level, the excitability of the inhibitory interneurons of the M1 rises as maximal movement speed declines [38]. Fatigue during the tapping test does not affect central muscular drive or force loss, and some evidence suggests it may involve motor rhythm creation [39]. In addition, exhaustion during an activity such as tapping may alter the activation-time sequence of agonist and antagonist muscles, with co-activation increasing as fatigue grows. This indicates that the muscles involved in moving the index finger are activated simultaneously, reducing their pace of execution [40].

Based on our results, it is reasonable to hypothesize that skeletal muscle fiber activation may be responsible for changes in reaction time. The chemical energy supplied by metabolic processes is converted into mechanical energy by the muscle fibers, which, working on the bone levels, culminate in movement. When the load is minimal, type I fibers are the most active, but type II fibers become more operative as the demand for force increases [41]. Muscle fibers expand when stimulated and contract when inactive [41]. This is because exercise causes an increase in myofibrils, which increases the size of muscle cells overall [42]. The central nervous system recruits motor units based on the size of the fibers, beginning with smaller and less powerful excitable fibers compared to bigger and more powerful fibers since the size of the fibers affects their potential to generate force. Phasic motor units, instead, include mayor-size motor neurons, have a higher interval discharge frequency, and have a much greater electrical pulse intensity. They are mostly located in the limb muscles [43]. Indeed, activities requiring dexterity, such as TT, engage the interosseous and lumbrical muscles of the hand via myoelectric stimulation induced by repetitive movement. The lumbar interosseous joint is the primary unit involved in TT movement. The interosseous muscles are palmar muscles and muscle occupies the space between the metacarpal bones. The lumbar muscles flex the metacarpophalangeal joints and extend the interphalangeal joints of the final four fingers of the hand [44].

In terms of RT reaction times, about 16% improvement in post-tapping was observed in 14 subjects, while about 9% worsening in RTA was observed in the remaining four subjects. The concept of viscoelasticity could provide an explanation for these findings. Viscoelasticity is the property of a substance to show both elastic and viscous behavior. Viscosity is directly related to temperature in an inverse relationship. That is, when temperature increases, viscosity decreases [45]. In muscles, a similar phenomenon occurs. The viscosity and hence the passive tension of the whole muscle structure are decreased by heating the muscle. As the muscle's elasticity decreases, its tendency to stretch increases [46]. TT acted as a stimulator or warm-up, increasing heart rate and, subsequently, blood and oxygen flow to the working muscle groups, warm-up also decreasing in energy rates activation of metabolic chemical reactions, in muscle blood flow and in muscle viscosity [47]. The TT test may promote the viscoelastic properties of the musculotendinous skeletal system. Temperature increase generates an enhancement in viscoelastic functions of the muscle, which allows for faster, more fluid movements with the recruitment of a greater number of muscle fibers deputed to work [48]. Thus, it is conceivable to assert that the viscoelasticity of the system is the primary contributor to the resulting enhancement in RTA. In conclusion, viscoelasticity decreases in heated muscle, resulting in increased flexibility and decreased rigidity, facilitating movements that require rapidity, as in the case of the two tests considered, for the assessment of reaction time.

VI. CONCLUSION AND FUTURE DEVELOPMENTS

Wearable sensors are becoming increasingly successful in motion analysis and are being used in more and more different fields. These devices are capable of conducting movement analysis that may be used in sports, clinical environments, and even as remote home care devices. Owing to these devices, it is simple to obtain fundamental data for analyzing the spatial and temporal behavior of different body districts. Non-intrusiveness with the topic being investigated is the characteristic that brought to light the effectiveness of IMU-sensor-based systems. This key effect arises from the natural analysis of motor data without causing discomfort to the user. As a result of technological innovation, these devices could serve as important aids in a wide range of investigations. In particular, this work focused on the application of an IMU sensor as a tool for motion analysis during the assessment of reaction time. The assessment of reaction time may offer in-depth information about the features of a subject of whatever age, which is also essential for enhancing cognitive and physical performance. This study was conducted following previous research that confirmed the reliability and validity of RT and TT measurements obtained with an IMU sensor. Based on the analysis of the data collected during TT, we derived features that can be indicators of fatigue during repeated exercise. Contrary to previous work in which specific execution times were set for the TT, the test was conducted at exhaustion and performed at the highest possible index finger excursion. The purpose of this imposition was to obtain a more noticeable angular coefficient, which is related to neuromuscular fatigue. The participants could initially start the TT test at maximal speed and within the lowest amplitude limitation (4 cm). Subsequently, the tapping speed of all individuals tended to decline, although they were able to extend the test maintaining the minimum amplitude. It was observed that TT works as a warm-up, allowing for RTA improvement. This allowed considering the sequence RT-TT-RT as an evaluation and training procedure and therefore proposing such a sequence along with the automation level and the adopted wearable device, as a novel protocol for sports people to be carried out and fastly assess their physical status and increase their focus on their main task (e.g., just before their sports performance). Potential future use of the methodology utilized in this work might be in the pathological sector. The work could be applied in the limb gesture assessment of patients with neurodegenerative disorders. Through the use of the sensor, the effects on movements due to a given program of physical activity, or drug treatment, could be assessed.

REFERENCES

[1] M. Alesi, A. Bianco, G. Luppina, A. Palma, and A. Pepi, "Improving children's coordinative skills and executive functions: The effects of a football exercise program," *Perceptual Motor Skills*, vol. 122, no. 1, pp. 27–46, Feb. 2016.

[2] H. Singh and A. Saini, "Relationship of coordinative ability with the skills of basketball," *Int. J. Yoga, Physiotheraphy Phys. Educ.*, vol. 2, no. 3, pp. 56–59, 2017.

[3] P. Arjun and K. Sunitha, "Effect of yoga training on coordinative abilities of high school students," *Int. J. Yogic, Huan Movement Sports Sci.*, vol. 4, no. 2, pp. 63–65, 2019.

[4] F. Latino, S. Cataldi, and F. Fischetti, "Effects of a coordinative ability training program on adolescents' cognitive functioning," *Frontiers Psychol.*, vol. 12, Jan. 2021, Art. no. 620440.

[5] I. Teodora-Mihaela, M. Veronica, and T. Laurentiu-Gabriel, "An investigation into the neuromuscular control at the level of the upper limbs of junior handball girls players," in *Proc. SHS Web Conf.*, vol. 26, 2016, p. 01039.

[6] P. Vairagade and G. Bhatt, "International journal of allied medical and clinical research (IJAMSCR)," *System*, vol. 9, no. 2, p. 7, 2021.

[7] L. H. Jakobsen, J. M. Sorensen, I. K. Rask, B. S. Jensen, and J. Kondrup, "Validation of reaction time as a measure of cognitive function and quality of life in healthy subjects and patients," *Nutrition*, vol. 27, no. 5, pp. 561–570, May 2011. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0899900710002509

[8] R. E. Reigal, S. Barrero, I. Martín, V. Morales-Sánchez, R. Juárez-Ruiz de Mier, and A. Hernández-Mendo, "Relationships between reaction time, selective attention, physical activity, and physical fitness in children," *Frontiers Psychol.*, vol. 10, p. 2278, Oct. 2019.

[9] M. Keshavarz and J. Dehghanizade, "The effects of gender and type of stimulus presentation on serial reaction time," *Int. J. Motor Control Learn.*, vol. 2, no. 4, pp. 20–29, 2020.

[10] S. K. Biswas, M. Paul, and J. S. Sandhu, "Role of sports vision and eye hand coordination training in performance of table tennis players," *Brazilian J. Biomotricity*, vol. 5, no. 2, pp. 106–116, 2011.

[11] Mackenzie. *Ruler Drop Test*. [Online]. Available: https://www.brianmac.co.uk/rulerdrop.htm

[12] T. Di Libero, C. Carissimo, A. Zagaglia, G. Cerro, L. Ferrigno, and A. Rodio, "Assessment of coordinative abilities through upper extremity wearable device technology," in *Proc. IEEE Int. Workshop Sport, Technol. Res. (STAR)*, Jul. 2022, pp. 175–179.

[13] M. Yahya, J. A. Shah, K. A. Kadir, Z. M. Yusof, S. Khan, and A. Warsi, "Motion capture sensing techniques used in human upper limb motion: A review," *Sensor Rev.*, vol. 39, no. 4, pp. 504–511, Jul. 2019.

[14] L. D. Vito, O. Postolache, and S. Rapuano, "Measurements and sensors for motion tracking in motor rehabilitation," *IEEE Instrum. Meas. Mag.*, vol. 17, no. 3, pp. 30–38, Jun. 2014.

[15] M. A. A. Zolkafi, N. J. Nordin, H. A. Rahman, N. A. M. Sarip, N. I. T. Abdullah, and M. A. Sahar, "Effect of 4-weeks traditional archery intervention on hand-eye coordination and upper limb reaction time among sedentary youth," *J. Social Sci. Res.*, vol. 6, pp. 1225–1230, Dec. 2018.

[16] C. Bokil, R. Bisen, and K. Kalra, ''Effectiveness of upper extremity proprioceptive training on reaction time in table tennis players,'' *Training*, vol. 5, p. 7, Jan. 2020.

[17] Y. O. Cakmak, B. Ozsoy, S. Ertan, O. O. Cakmak, G. Kiziltan, H. Yapici-Eser, E. Ozyaprak, S. Olcer, H. Urey, and Y. Gursoy-Ozdemir, ''Intrinsic auricular muscle zone stimulation improves walking parameters of Parkinson's patients faster than Levodopa in the motion capture analysis: A pilot study,'' *Frontiers Neurol.*, vol. 11, Oct. 2020, Art. no. 546123.

[18] O. K. Wadoo, S. I. Sayeed, and M. Rouf, ''Effect of gender and physical activity on visual and auditory reaction time in young adults,'' *Int. J.*, vol. 2, no. 2, p. 462, 2019.

[19] D. Rudolf and V. Triyanti, ''Designing a device for measuring human reaction time,'' *IOP Conf. Ser., Mater. Sci. Eng.*, vol. 847, no. 1, 2020, Art. no. 012051.

[20] C. Grigoroiu, T. Wesselly, R. A. Pelin, and A. Pricop, ''The evaluation of the complex reaction time at the upper limbs level of students in technical higher education by utilizing computerized testing,'' *eLearning Softw. Educ.*, vol. 3, pp. 1–12, Mar. 2018.

[21] N. Akram, H. Li, A. Ben-Joseph, C. Budu, D. A. Gallagher, J. P. Bestwick, A. Schrag, A. J. Noyce, and C. Simonet, ''Developing and assessing a new web-based tapping test for measuring distal movement in Parkinson's disease: A distal finger tapping test,'' *Sci. Rep.*, vol. 12, no. 1, pp. 1–11, Jan. 2022.

[22] C. G. Goetz et al., ''Movement disorder society-sponsored revision of the unified Parkinson's disease rating scale (MDS-UPDRS): Process, format, and clinimetric testing plan,'' *Movement Disorders*, vol. 22, no. 1, pp. 41–47, 2007.

[23] K. S. van Schooten, L. Duran, M. Visschedijk, M. Pijnappels, S. R. Lord, J. Richardson, and K. Delbaere, ''Catch the ruler: Concurrent validity and test–retest reliability of the ReacStick measures of reaction time and inhibitory executive function in older people,'' *Aging Clin. Experim. Res.*, vol. 31, no. 8, pp. 1147–1154, Aug. 2019.

[24] T. Di Libero, E. Langiano, C. Carissimo, M. Ferrara, P. Diotaiuti, and A. Rodio, ''Technological support for people with Parkinson's disease: A narrative review,'' *J. Gerontol. Geriatrics*, vol. 2022, pp. 1–15, Jan. 2022.

[25] P. Rivera, E. Valarezo, M.-T. Choi, and T.-S. Kim, ''Recognition of human hand activities based on a single wrist IMU using recurrent neural networks,'' *Int. J. Pharma Med. Biol. Sci.*, vol. 6, no. 4, pp. 114–118, 2017.

[26] MbientLab. *Metamotionrl*. Accessed: May 28, 2023. [Online]. Available: https://mbientlab.com/metamotionrl/

[27] MbientLab. *MetaBase App*. Accessed: May 28, 2023. [Online]. Available: https://mbientlab.com/tutorials/MetaBaseApp.html

[28] MATLAB. *Find Abrupt Changes*. Accessed: May 28, 2023. [Online]. Available: https://it.mathworks.com/help/signal/ref/findchangepts.html

[29] MATLAB. *Find Peaks*. Accessed: May 28, 2023. [Online]. Available: https://it.mathworks.com/help/signal/ref/findpeaks.html

[30] M. Friedman, ''A comparison of alternative tests of significance for the problem of *m* rankings,'' *Ann. Math. Statist.*, vol. 11, no. 1, pp. 86–92, 1940, doi: 10.1214/aoms/1177731944.

[31] *Practical Nonparametric Statistics, 3rd Edition | Wiley*. Accessed: May 28, 2023. [Online]. Available: https://www.wiley.com/en-us/Practical+Nonparametric+Statistics%2C+3rd+Edition-p-9780471160687

[32] A. Ross and V. L. Willson, *Paired Samples T-Test*. The Netherlands, Rotterdam: Sense Publishers, 2017, pp. 17–19, doi: 10.1007/978-94-6351-086-8_4.

[33] J. Rothwell, A. Antal, D. Burke, A. Carlsen, D. Georgiev, M. Jahanshahi, D. Sternad, J. Valls-Solé, and U. Ziemann, ''Central nervous system physiology,'' *Clin. Neurophysiol.*, vol. 132, no. 12, pp. 3043–3083, 2021.

[34] C. T. F. Tse, A. C. McDonald, and P. J. Keir, ''Adaptations to isolated shoulder fatigue during simulated repetitive work. Part I: Fatigue,'' *J. Electromyogr. Kinesiol.*, vol. 29, pp. 34–41, Aug. 2016.

[35] D. Srinivasan and S. E. Mathiassen, ''Motor variability in occupational health and performance,'' *Clin. Biomechanics*, vol. 27, no. 10, pp. 979–993, Dec. 2012.

[36] E. Madinabeitia-Mancebo, A. Madrid, A. Oliviero, J. Cudeiro, and P. Arias, ''Peripheral-central interplay for fatiguing unresisted repetitive movements: A study using muscle ischaemia and M1 neuromodulation,'' *Sci. Rep.*, vol. 11, no. 1, pp. 1–13, Jan. 2021.

[37] A. Vila-Villar, M. Naya-Fernández, A. Madrid, E. Madinabeitia-Mancebo, V. Robles-García, J. Cudeiro, and P. Arias, ''Exploring the role of the left DLPFC in fatigue during unresisted rhythmic movements,'' *Psychophysiology*, vol. 59, no. 10, Oct. 2022, e14078.

[38] A. Madrid, E. Madinabeitia-Mancebo, J. Cudeiro, and P. Arias, ''Effects of a finger tapping fatiguing task on M1-intracortical inhibition and central drive to the muscle,'' *Sci. Rep.*, vol. 8, no. 1, pp. 1–10, Jun. 2018.

[39] C. G. Brownstein, L. Espeit, N. Royer, T. Lapole, and G. Y. Millet, ''Fatigue-induced changes in short-interval intracortical inhibition and the silent period with stimulus intensities evoking maximal versus submaximal responses,'' *J. Appl. Physiol.*, vol. 129, no. 2, pp. 205–217, Aug. 2020.

[40] P. Arias, V. Robles-García, N. Espinosa, Y. Corral, and J. Cudeiro, ''Validity of the finger tapping test in Parkinson's disease, elderly and young healthy subjects: Is there a role for central fatigue?'' *Clin. Neurophysiol.*, vol. 123, no. 10, pp. 2034–2041, Oct. 2012.

[41] R. Qaisar, S. Bhaskaran, and H. Van Remmen, ''Muscle fiber type diversification during exercise and regeneration,'' *Free Radical Biol. Med.*, vol. 98, pp. 56–67, Sep. 2016.

[42] G. Paulsen, K. Vissing, J. M. Kalhovde, I. Ugelstad, M. L. Bayer, F. Kadi, P. Schjerling, J. Hallén, and T. Raastad, ''Maximal eccentric exercise induces a rapid accumulation of small heat shock proteins on myofibrils and a delayed HSP70 response in humans,'' *Amer. J. Physiol.-Regulatory, Integrative Comparative Physiol.*, vol. 293, no. 2, pp. R844–R853, Aug. 2007.

[43] E. Henneman, G. Somjen, and D. O. Carpenter, ''Functional significance of cell size in spinal motoneurons,'' *J. Neurophysiol.*, vol. 28, no. 3, pp. 560–580, May 1965.

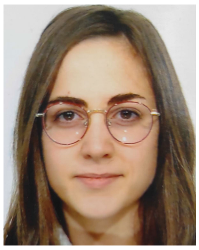
[44] T. Schreuders, J. Brandsma, and H. Stam, ''The intrinsic muscles of the hand,'' *Physikalische Medizin, Rehabilitationsmedizin, Kurortmedizin*, vol. 17, no. 1, pp. 20–27, 2007.

[45] I. Pajic-Lijakovic, ''The basic concept of viscoelasticity,'' in *Viscoelasticity and Collective Cell Migration*. Amsterdam, The Netherlands: Elsevier, 2021, pp. 21–46.

[46] D. G. Behm, A. J. Blazevich, A. D. Kay, and M. McHugh, ''Acute effects of muscle stretching on physical performance, range of motion, and injury incidence in healthy active individuals: A systematic review,'' *Appl. Physiol., Nutrition, Metabolism*, vol. 41, no. 1, pp. 1–11, Jan. 2016.

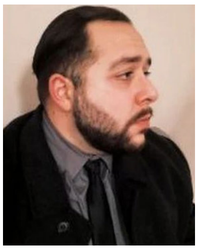
[47] F. G. Shellock and W. E. Prentice, ''Warming-up and stretching for improved physical performance and prevention of sports-related injuries,'' *Sports Med.*, vol. 2, no. 4, pp. 267–278, 1985.

[48] J. Opplert and N. Babault, ''Acute effects of dynamic stretching on mechanical properties result from both muscle-tendon stretching and muscle warm-up,'' *J. sports Sci. Med.*, vol. 18, no. 2, p. 351, 2019.



CHIARA CARISSIMO (Graduate Student Member, IEEE) received the master's degree in electrical engineering from the University of Cassino and Southern Lazio, Cassino, Italy, in 2019, where she is currently pursuing the Ph.D. degree in methods, models, and technologies for engineering. She got a research grant from the University of Salerno, from May 2020 to December 2020. Her research interests include the detection of movement disorders using measurements from wearable devices, the implementation of machine learning algorithm to analyze data, and to classify movement disorders in patients with neurodegenerative diseases.

GIANNI CERRO (Member, IEEE) is currently a Research Fellow with the Department of Medicine and Health Sciences ''Vincenzo Tiberio,'' University of Molise, Italy. His research interests include magnetic localization systems for biomedical and industrial applications, cognitive radio systems for new-generation communication technologies, measurements in telecommunication networks, sensor networks for environmental monitoring, and the measurement characterization of medical devices, such as brain–computer interfaces.



TOMMASO DI LIBERO (Graduate Student Member, IEEE) received the master's degree in preventive and adapted exercise science and techniques (Class LM-67) from the University of Cassino and Southern Lazio, Cassino, Italy, in 2019, where he is currently pursuing the Ph.D. degree in methods, models, and technologies for engineering. His research interests include the advantages of the implementation of wearable devices for movement tracking and analysis in medical and sports environments.

LUIGI FERRIGNO (Senior Member, IEEE) has been a full professor in electric and electronic measurement, since 2020, and the Scientific Manager of the Industrial Measurements Laboratory, University of Cassino, Cassino, Italy, since 2004. In 2008, he was a Founding Member of the university spin-off, Spring Off (University of Salerno), Fisciano, Italy. He is currently an NDE4.0 Ambassador for the Italian Association of Non-Destructive Evaluation and Test (AiPnD) in the EFNDT WG10. He has coordinated and participated in several national and international research projects. His current research interests include the NDT4.0, novel learning sensors and measurement systems for smart city, the Internet of Things (IoT), automotive, smart energy, and environment.

ALESSANDRO MARINO (Senior Member, IEEE) was born in Potenza, Italy. He received the M.Sc. degree (cum laude) in computer science from the University of Naples Federico II, Naples, Italy, in 2006, and the Ph.D. degree in industrial innovation engineering from the University of Basilicata, Potenza, in 2010. He is currently an Associate Professor with the Department of Electrical and Information Engineering, University of Cassino and Southern Lazio. In 2011, he was an Assistant Professor in automatic control with the University of Salerno, Fisciano, Italy. In 2011, he was a Visiting Scholar with the Institute for Systems and Robotics, Instituto Superior Tecnico, Lisbon, Portugal. In 2007, he was a Visiting Scholar with the University of Tennessee, Knoxville, TN, USA. His current research interests include the modeling and control of robotic systems, trajectory planning, industrial automation, multi-robot systems, marine robotics, and distributed control, fault detection, and isolation.

ANGELO RODIO received the M.D. and Ph.D. degrees. He has been a Research Fellow in physiology with the University of Cassino and Southern Lazio, Cassino, Italy, since 2001. From 2010 to 2013, he was a member of the Scientific Council and the Department Representative of the University of Cassino and Southern Lazio, where he is also the Director of the Laboratory "Sustainable living concept Xlab–Marco Marchetti." Since 2017, he has been the Project Manager and a Coordinator in collaboration with the Medex Human Physiology Laboratory for the functional assessment and programming of role-specific training. He was a Scientific Coordinator for different sports societies, such as S. S. Lazio Football (1998–2003) and Mascalzone Latino Consortium (2002–2007).

Open Access funding provided by 'Università degli Studi di Cassino e del Lazio Meridionale' within the CRUI CARE Agreement