Journal of Physical Education and Sport ® (JPES), Vol. 24 (issue 5), Art 122, pp. 1066 - 1073, May 2024
online ISSN: 2247 - 806X; p-ISSN: 2247 – 8051; ISSN - L = 2247 - 8051 © JPES

Original Article

Acceleration analysis and detection algorithm for burpees

ĽUBOSLAV ŠIŠKA[1], DANIEL ŽIDEK[2], ŠTEFAN TKAČIK[3], GHEORGHE BALINT[4]
[1] Department of Physical Education and Sports, Catholic University in Ružomberok, SLOVAK REPUBLIC
[3] Department of Informatics, Catholic University in Ružomberok, SLOVAK REPUBLIC
[4] Department of Physical Education and Sport Performance, Faculty of Movement, Sports and Health Sciences, University Vasile Alecsandri of Bacau, ROMANIA

Published online: May 31, 2024
Accepted for publication : May 15, 2024
DOI:10.7752/jpes.2024.05122

Abstract:
With the advancement of technology, it is now possible to accurately record and evaluate various physical exercises. In this study we measured acceleration values during the burpee exercise, developed an algorithm to detect it based on recorded data, and assessed its intensity. Ten test subjects (aged 21.1±1.60 years, height 181.6±10.69 cm and weight 76±12.30 kg) participated in research, performing a total of 60 burpees (6 each) to a sound signal at 7 seconds intervals. The acceleration values were collected using the PHYPHOX mobile app. with the phone attached to the test subject's left arm just below the deltoid muscle. Data from the application were transferred a computer screen, positioned next to the test subject, and then exported to MS Excel. The highest acceleration values of up to 62 ms-2 were achieved in the first phase of the exercise when the palms hit the floor during the transition to the push-up. Slightly lower acceleration values were recorded during the transition from the push-up to the squat and when landing on the ground after a jump. The extension of the legs after landing on the ground was marked as the end of exercise. We used the moving average smoothing method to filter the values from the individual English squats. The beginning of the exercise was identified by the smoothed acceleration value exceeding the limit of 0.5 and not falling below this limit for the next 200 values. The end of the exercise was identified in a similar way, but from the opposite side: the acceleration value had to exceed the limit value of 3 ms^(-2) and the next 200 values did not fall below this threshold. This way, we managed to identify the necessary data with 99% accuracy. We expressed the intensity of the Burpee as an average of the corresponding values, and it ranged from 4.06 to 11.37 ms^(-2). The research results will be used to diagnose specific motor performance.
Key Words*:* mobile application, exercise intensity, video analysis

Introduction

Technological progress has an impact on various areas of knowledge, including sports science and other broader areas of life. The demand to study the technological innovations rises with their increasing popularity, especially within the sports industry. Technology provides many advantages in the field of sports and sports science and it allows us to record and evaluate the progress of various physical exercises. (Mali, 2020; Kos, 2018; Grun, 2011).

We must ask ourselves three basic questions when studying the impacts of modern technologies on sports and physical activity.

1. What parameters are we going to monitor?
2. During which exercise will we monitor the selected parameters?
3. How are we going to record and evaluate the data?

Acceleration is one of the critical factors for achieving excellent results in sports. Its analysis has a decisive impact on the evaluation and improvement of sports performance (Pernek, 2015). The ability to change speed and direction through acceleration and deceleration are important attributes for a successful performance in many team sports (Dragijsky, 2016). Starting from a static position (acceleration) is often crucial for soccer players because it allows them to react quickly to changes in the game and win an advantage over the opponent. This can be decisive when fighting for the ball, escaping the defense or making quick turns while dribbling. Measuring acceleration provides the coaches with valuable information about the players' fitness, training effectiveness and in-match performance. These data can then be used to optimize the training programs (Delaney, 2018). Acceleration is also interesting in other sports, e.g. during the strikes in combat sports or in table tennis (Izzo, 2023a; 2023b).

The relationship between sprint acceleration and the level of various fitness parameters was also demonstrated (Afandi, 2021; Sahin, 2014). Based on the above, we consider acceleration to be an ideal parameter that can be used to assess the course and intensity of physical activity.

Corresponding Author: GHEORGHE BALINT, E-mail: gbalint@ub.ro

If we focus on the selection of exercises, we must take into account their simplicity, complexity and ease in terms of the use of additional equipment. The "burpee" (or the English squat), which was invented by R. N. Burpee in the 1920s, is one of the most popular physical exercises of today. It is well-known all around the world, and games and competitions associated with the burpee are held worldwide (Pelovoy, 2023). It is a functional exercise that combines squats, planks, push-ups and lunges, and it is one of the most effective fat burning exercises. When a proper technique is used, all major muscle groups of the body, including the chest, back, legs and abdomen, are activated. This exercise does not require special or heavy equipment, as it is performed directly with one's own weight (Podstawski, 2013; Tai, 2022). It is also important to consider whether the exercise can be done in various speeds of execution, which is directly related to acceleration.

The burpees themselves have been used in many research studies either as part of a diagnostic test (Moura, 2016; Kojic, 2021; Podstawski, 2019), but only in terms of the number of repetitions in which the speed of performing the exercise was decisive. Other uses of the burpee include the development of movement capacity (Cepulenas, 2011; Masagca, 2024), and the physiological response of the body was also assessed when the exercise was performed as part of a HIIT program (Perez-ifran, 2022; Bingley, 2019; Mayr Ojeda, 2022). However, we did not find any research where individual repetitions would be assessed in terms of the course and intensity of execution. The variability of use suggests that the burpee is an ideal exercise that can be assessed through acceleration.

The third question related to recording, analyzing and evaluating a given exercise can be addressed through new approaches in monitoring the exercise intensity with the help of wearable devices and mobile applications that can monitor and evaluate exercise intensity on an individual level with integrated sensors, thus contributing to more accurate planning of physical activity (Sahlan, 2019). If we consider the fact that the majority of the population own a mobile phone, it is the easiest way to track acceleration. In recent times, mobile phones have often been used as measurement tools in physics, university laboratories and schools. These phones were usually equipped with an accelerometer, gyroscope, magnetometer, pressure sensor and a microphone. Until recently, apps could only export raw data into a table. In addition to recording the data from sensors, the PHYPHOX app can process the data from sensors in real time, and in some settings also in advance. In the user interface, it is possible to set up a new experiment with the relevant type of processing and presentation of measurements. The app also allows the users to share the smartphone screen with another device, such as a desktop computer (Pierratos, 2020). Detection of motor activities using the accelerometer in a mobile phone is commonly used in many apps and devices to track physical activity and exercise. The accelerometer can be used to detect steps. Different activities, such as running, cycling, walking up/down the stairs, etc., have specific movement patterns that can be recognized by analyzing the accelerometer data. In order to achieve an accurate detection of the motion activity using an accelerometer, it is often necessary to use a combination of data processing algorithms (Brezmes, 2009; Khan, 2010). It is important to use the transformed acceleration data, which are independent of the position of the phone (Heng, 2016). This option is also offered by the PHYPHOX app. In our case, we want to detect a single repetitive exercise and measure its intensity, which can be achieved by averaging the values. When comparing acceleration and exercise intensity measured by VO2max, average acceleration values over a certain period of time are commonly used (Ng, 2024). In this case, we need to accurately identify the beginning and end of the exercise and the associated acceleration values. With the help of video analysis, which is an integral part of sports research (Wang, 2004), it is possible to match the acceleration data with the exact position of the body during exercise when a phone is linked to the video projector. This results in the goal of the work to analyze the course of acceleration values during the burpee and create an algorithm for its detection when evaluating specific motor performance.

Material & methods

Study design

In our research, we used kinematic video analysis supplemented with data tracking from an accelerometer. The study included the analysis of 60 Burpees from 10 test subjects (6 repetitions each) aged 21.1±1.60 yr., height 181.6±10.69 cm and weight 76±12.30 kg. The test subjects did not suffer from orthopedic and neurological injuries.

The procedures presented were in accordance with the ethical standards on human experimentation and in compliance with the Helsinki Declaration. All subjects were informed about the potential risks and signed a written informed consent before data collection. Burpees were performed independently at a sound signal at an interval of 7 seconds, and the test subjects were instructed not to exert significant movement activity between the repetitions. The course of one sequence (Burpee) consisted of the basic position (standing upright), from which the test subject moved after the sound signal into the lying position (plank) with outstretched or slightly bent arms in the shortest possible time, followed by the second phase, i.e. a transition from the lying position into a jump and back to the basic position (standing upright).

The acceleration values were collected using the PHYPHOX mobile app with the mobile phone in a case attached to the test subject's left arm just below the deltoid muscle. The PHYPHOX app recorded the accelerations along the x,y,z axes and the overall acceleration magnitude m=√(x^2+y^2+z^2) in ms^(-2) with the relevant time stamps. The values were recorded without the gravity g component and when the mobile device was motionless, the acceleration values had a zero value in all positions. In our research, a Sony Xperia XZ2 was used with a recording frequency of 206. 7 Hz. The measurement data were exported into csv and MS Excel, with the first column containing the time values, followed by the accelerations on the x and y axis and the total m (phyphox.org). The values displayed on the mobile phone were transferred to the PC desktop using SCRPY (or Screen Copy), a free and open-source application that allows to display and control an Android device from a PC. It uses an ADB connection via USB and does not require rooted devices. SCRCPY has very low latency, meaning there is little to no delay between the device and the computer (scrpy.org). The PC screen was then projected onto a screen at a distance of 4 meters using a data projector.

The entire process was video recorded on an iPhone 12 mini with a recording frequency of 120 fps (frames per second). The camera was placed at a height of 80 cm from the floor at a distance of 3.5 meters from the exercising test subject and it simultaneously recorded the test subject performing the exercise and the right part of the projected screen where the corresponding acceleration values were displayed (Fig. 1).

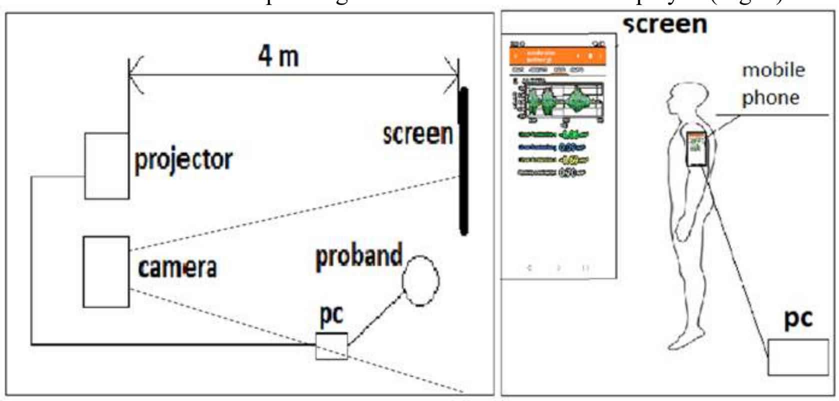

Fig. 1 Schematic representation of the research situation (top view and camera view)

Statistical analysis

In our research, we worked with the values of total acceleration magnitude m. The data were processed in three steps. In the first step, we identified the data that were displayed below each other on the x,y,z andm axis at a specific time in the video recording. We have explicitly assigned these four numbers to the four numbers exported to MS Excel. This way, we paired the time data from the video to the accelerometer and created an auxiliary timeline in seconds where each value from MS Excel was assigned to the specific frame in the video recording. This practically meant that the time data from the accelerometer were reformatted to the time data from the video recording. In the second step, we selected the data corresponding to the individual English squats according to the timeline, and in the third step, we conducted the statistical analysis itself.

The collected data were analyzed using descriptive statistics: mean (M), standard deviation (SD), maximum (max) and minimum (min). Pearson's (r) and ICC correlation was used to determine the relationships between the variables. The significance levels were atp $< 0,05$ and $p < 0,01$. The data pertaining to the individual repetitions of the English squat were extracted by smoothing the values using a moving average. The statistical analyses were performed in MS Excel 2016, IBM SPSS 22 and JASP 0.16.4.0.

Results

Approximately 8,000 acceleration values were recorded during testing, with approximately 400 to 900 values per repetition. We have identified three significant moments that divide the exercise into the individual phases. The first phase spanned from the beginning of the exercise through the transition to the squat, the contact of the palms with the floor and ended with the loss of contact between the feet and the floor. At this moment, the highest acceleration values of up to 62 ms-2 were achieved. The second phase consisted of the transition to a push-up and ended with the transition to a squat and the loss of contact between the palms and the floor. The third phase consisted of a transition to the standing position, followed by a jump and it ended with a landing on the floor, which was also accompanied by high acceleration values. After landing on the ground, there was a slight swaying and stretching of the legs, which concluded the exercise cycle. In terms of time, the first phase was the shortest, and the second and third phase had approximately the same duration (Fig. 2).

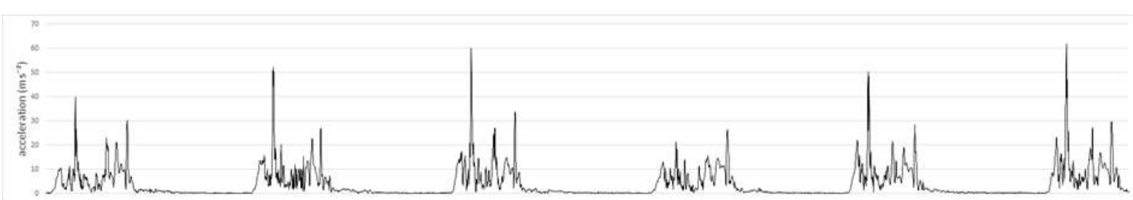

Fig. 2 Visual representation of the acceleration values during testing

When filtering the values representing the Burpee, we used the moving average smoothing method. To eliminate the unwanted external factors, an average of 11 values (5 before and 5 after the given value) was used instead of the given value, and the data were smoothed 9 times with this method. The beginning of the exercise was identified by the smoothed acceleration value exceeding the limit of 0.5 and not falling below this limit for the next 200 values. The end of the exercise was identified in a similar way, but from the opposite side, and in three possible ways: the acceleration value had to exceed the limit value of 1 ms^(-2) (burpeeend1), 2 ms^(-2) (burpeeend2) or 3 ms^(-2) (burpeeend3) and the next 200 values did not fall below this threshold. The resulting intensity was calculated as the average of the values (recorded by the PHYPHOX app) representing one burpee repetition. When evaluating a specific case, the English squat was identified according to video analysis, which consisted of 499 values, and the resulting intensity, i.e. the average acceleration, was 10.75 ms^(-2) . However, when filtering the values using a moving average, the start of the exercise was identified with a deviation of 33 values before the actual start of the exercise. The end of the exercise was shifted compared to the actual values: in the case of burpeeend1, the deviation was 11 values beyond the real end, the burpee consisted of 543 values and the intensity was at the level of 9.71 ms^(-2). In the case of burpeeend2, the deviation was 16 values before the actual end, the burpee consisted of 516 values and the intensity was at the level of 10.17 ms^(-2) . With burpeeend3, the deviation was 31 values before the actual end, the burpee consisted of 501 values and the intensity was at the level of 10.37 ms^(-2) (Fig. 3).

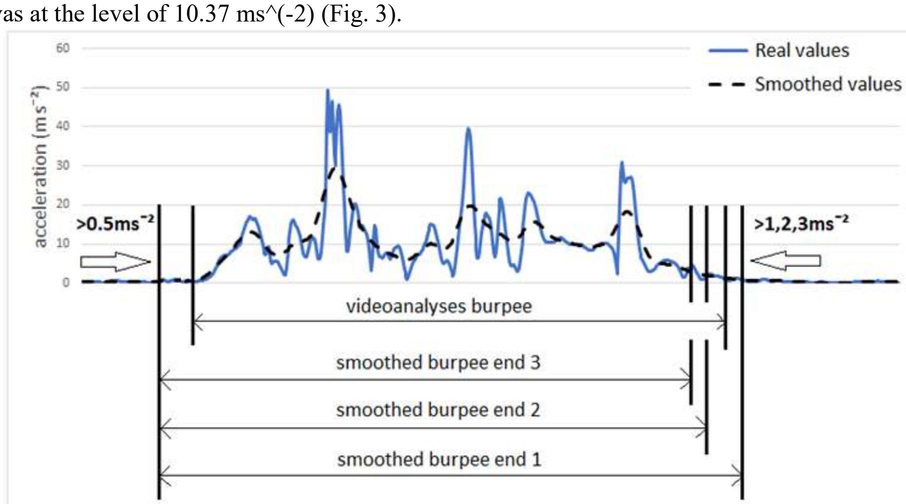

Fig. 3 The course of the burpee based on the actual and smoothed values

When filtering the values, the deviations took on a positive or negative course depending on the fact whether they were before or after the actual start and end of the exercise in the numeric column. In the individual filtering methods (increased acceleration above the value of 1, 2 and 3 ms-2), incorrect detection of the beginning and end of the exercise also occurred due to the test subject's involuntary movements between the repetitions. In the burpeeend1 detection method, altogether 20 of the 60 burpee repetitions observed were incorrectly identified. The detection of the beginning of the exercise showed a deviation ranging from -885 to 1577 values with an average of 247 values; the deviation in the detection of the exercise end ranged from -1924 to 1337 values with an average of 122 values. In burpeeend2, a total of 9 burpee repetitions were misidentified. The detection of the beginning of the exercise showed a deviation ranging from -6 to 1437 values with an average of 157 values; the deviation in the detection of the exercise end ranged from -610 to 1437 values with an average of 113 values. All burpee repetitions were correctly identified in the burpeeend3 method. The detection of the beginning of the exercise showed a deviation ranging from -6 to 93 values with an average of 7 values; the deviation in the detection of the exercise end ranged from -146 to 174 values with an average of 7 values (Fig. 4).

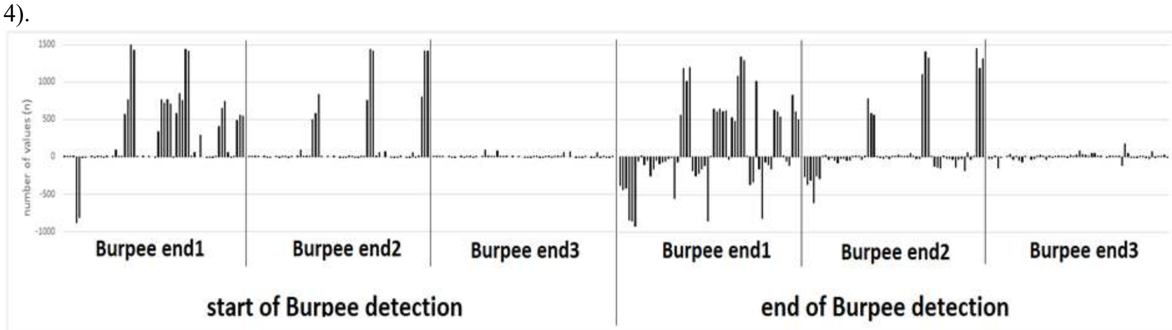

Fig. 4 Deviations from the actual state when filtering the acceleration values

After the comparison of the actual number of values belonging to the individual burpee repetitions identified by video analysis (RE) and the number of values filtered by smoothing the moving average, the burpeeend1 and burpeeend2 method (E1, E2) did not show significant agreement ICC $p > .05$. In the burpeeend3 method (E3), the number of values was almost identical to the actual conditions ICC = .98, CI .91 - .99, $F(59,59) = 19.21$, $p < .01$. When comparing the intensity, the burpeeend1 method did not show a significant agreement with the actual conditions ICC $p > .05$. The burpeeend2 method demonstrated significant agreement ICC = .76, CI .59 - .86, $F(59,59) = 4.12$, $p < .01$. In the burpeeend3 method (E3), the resulting intensity was almost identical to the actual conditions ICC = .99, CI .98 - .99, $F(59,59) = 90.21$, $p < .01$., as was the case in the number of values. The dependence between the number of values and the resulting intensity of the exercise was demonstrated with actual values $r(118) = -.82$, $p < .01$ as well as with the method of filtering the burpeeend3 values $r(118) = -.80$, $p < .01$ (Tab. 1).

Table. 1 Number of values and intensity of the English squat with different detection methods and their comparison

	M	SD	Min	Max	ICC	r
Number of values						
RE	599.20	95.36	461	941		
E1	724.03	244.90	222	1432	RE-E1 N.S.	
E2	642.85	160.71	172	1180	RE-E2 N.S.	
E3	598.57	86.77	454	837	RE-E3 **	RE-RE **
Intensity						E1-E1 N.S.
RE	7.79	1.65	4.06	11.37		E2-E2 N.S.
E1	4.34	3.00	0.17	10.31	RE-E1 N.S.	E3-E3 **
E2	6.76	2.34	0.32	10.71	RE-E2 **	
E3	7.79	1.58	4.31	10.85	RE-E3 **	

Notes: RE - number of values and intensity determined according to video analysis, E1 - number of values and intensity determined according to the burpeeend1 method, E2 - number of values and intensity determined according to the burpeeend2 method, E3 - number of values and intensity determined according to the burpeeend3 method

Dicussion

The aim of our study was to analyze acceleration values during the Burpee and propose an algorithm for its detection. Our work is the first one that deals with this exercise in such detail. Our research has been focusing on the burpee for quite some time. It is mainly due to the complexity of this exercise and the possibility to influence its strength and endurance potential. Another advantage is the duration of the Burpee, which opens up new possibilities in the design of short-interval movement programs. In the past, we focused on the use of the Burpee in fitness training (Šiška, 2017; Šiška, 2020) and we investigated the time and intensity required to perform the exercise, but the data acquisition process was complicated in terms of the necessary equipment. We wanted to find an easier way to diagnose performance in this exercise, and the mobile phone turned out to be the perfect choice. The PHYPHOX app offers trouble-free recording of acceleration values, which can be exported into the csv format, which is readable in MS Excel. Attaching the phone to the body using a commonly available case is also very easy.

If we focus on the Burpee as part of a diagnostic test, the methodology of execution varied. In Kojic (2021) and Podstawski (2013, 2019), the burpee was executed without the push-up into the plank on outstretched arms, no jump was done afterwards and the exercise ended with a transition to an upright position with a hand clap above the head. Although the methodology was not described in detail, Moura (2016) used Burpees both with the push-up and jump. Similarly, in Perez-ifran (2022) and Mayr Ojeda (2022), the burpee was performed in its entirety with the push-up and jump. In our research, we decided to perform the burpee with a jump, but we instructed the test subjects not to raise their arms above their heads. Similarly, the test subject didn't have to do a push-up and could have his/her arms extended or slightly bent during the plank phase. This variant was chosen because of its speed, which was our focus. A slight bending of the arms activated the spring mechanisms and the test subjects could develop a higher intensity. The intensity parameter seems crucial to us especially if the exercise is always performed only after a single repetition, but with maximum effort. In this case, the logical decision was to monitor the acceleration during the exercise.

Based on our unpublished preliminary research, we conclude that the acceleration values recorded by the PHYPHOX app reflect the intensity of the exercise fairly well, but we could not determine exactly which values correspond to the individual body positions and precisely define the beginning and end of the exercise. This was the main reason for carrying out our research. The assumptions from the preliminary measurements were confirmed and the course of the acceleration during the exercise reflected the intensity of execution. The test subjects were instructed to perform the first Burpee slowly, the second one quickly, and the third one with maximum effort. Not all test subjects performed the exercise according to these instructions, but the graph shows clear differences between the repetitions. However, our current research was not focused on different intensities because these were not its main goal, and will be assessed in detail in upcoming research. For greater clarity, we divided the exercise into individual phases, which show that the highest acceleration values are achieved when the palms hit the floor and the feet lose contact with the floor. The transition to the push-up and to the squat was the least intense. High acceleration values were also observed in the third phase, which had the highest intensity. The most essential task for our subsequent research was to be able to quickly filter out the data representing the Burpee. We managed to achieve this goal by smoothing the values using a moving average. Although there are many approaches to identify and recognize motor activity based on neural networks, artificial intelligence, etc. (Brezmes, 2009; Khan, 2010; Gupta, 2022; Kulsoom, 2022), we wanted to work further with the data and therefore decided to work in MS Excel.

At the beginning of the research, we tackled the issue of simultaneously seeing the exercising test subject and the phone screen in a format that allows us to identify the acceleration values. We connected the phone to the computer with a data cable and displayed the screen content using Screencopy. Then, using a projector, we displayed the data from the phone on a screen placed next to the exercising test subject. The second issue was related to the assignment of exported values in MS Excel to individual body movements. We created an auxiliary timeline based on the time data from the accelerometer, but this timeline did not exactly match the timeline from the video recording due to the different frequency of the recording. The application recorded 200 values per second and the video was recorded at 120 frames per second. In case of time data mismatch, we worked with the value that was currently displayed on the video recording. The detection algorithm was designed as follows: the values recorded by the PHYPHOX app were inserted into the first MS Excel column, the smoothed values were inserted in the next 9 columns, the detections of the beginning and end of the exercise were shown as true/false in the next two columns, and the next column contained the specific lines where the exercise started and ended. In the last column, the average of the values corresponding to one burpee repetition was calculated. The individual methods of detection (burpeeend1, 2, 3) showed significant differences. The burpeeend1 and burpeeend2 method identified all repetitions correctly, but also marked the burpee values incorrectly, and this resulted in enormous deviations from the actual state. We considered only the first 60 detected repetitions in the analysis. The burpeeend3 method showed high consistency, it identified all the repetitions correctly, and the deviations from the actual state were acceptable. According to the video analysis, there were from 461 to 941 values per Burpee, which corresponded to an intensity from 4.06 ms^(-2) to 11.37 ms^(-2). In the case of burpeeend3, we reached almost identical results and the resulting significant correlations. With this method, we were able to identify 99% of the data corresponding to the burpee, but this finding will definitely have to be verified on a larger sample. We hypothesized that the faster the burpee (fewer corresponding values), the higher the intensity, which was also confirmed by the actual values identified in the video analysis as well as by the burpeeend3 method, but not absolutely. This finding suggests that the intensity may slightly differ even when the burpees are performed at the same speed.

Conclusions

We conclude that we managed to analyze the course of acceleration during the Burpee. With the help of video analysis, we were able to identify the individual phases and the total length of the Burpee, and we determined its intensity as an average of the corresponding values.

We found a way to quickly filter the values representing the Burpee. The intensity of Burpee, which was calculated based on video analysis and using the moving average smoothing, was a 99% match. The research results will be used to diagnose specific motor performance.

This paper is part of the VEGA 1/0482/21 research grant "Standardization of specific short-interval load as a motor test of strength-endurance abilities in combat sports"

Conflicts of interest - If the authors have any conflicts of interest to declare.

References:

Afandi, M. A. M., Mohamad, N. I., Fazila, N., Malek, A., Chinnasee, C., & Nadzalan, A. M. (2021). The Relationship between Core Strength Performance with Sprint Acceleration. *In Journal of Physics: Conference Series* (Vol. 1793, No. 1, p. 012056). IOP Publishing.

Bingley, S., Witchalls, J., McKune, A., & Humberstone, C. (2019). Sprint running & burpees: comparison of acute physiological and neuromuscular effects of two high intensity interval training protocols. *Journal of Science and Medicine in Sport*, 22, S31.

Brezmes, T., Gorricho, J. L., & Cotrina, J. (2009). Activity recognition from accelerometer data on a mobile phone. *In Distributed Computing, Artificial Intelligence, Bioinformatics, Soft Computing, and Ambient Assisted Living: 10th International Work-Conference on Artificial Neural Networks*, IWANN 2009 Workshops, Salamanca, Spain, June 10-12, 2009. Proceedings, Part II 10 (pp. 796-799). Springer Berlin Heidelberg.

Čepulėnas, A., Bružas, V., Mockus, P., & Subačius, V. (2011). Impact of physical training mesocycle on athletic and specific fitness of elite boxers. *ARCH BUDO*, 7

Delaney, J. A., Cummins, C. J., Thornton, H. R., & Duthie, G. M. (2018). Importance, reliability, and usefulness of acceleration measures in team sports. *The Journal of Strength & Conditioning Research, 32(12)*, 3485-3493.

Dragijsky, M., Maly, T., Bujnovsky, D., Zahalka, F., Hank, M., & Mala, L. (2016). Level and differences of sprint acceleration among soccer players in three different age categories. *Journal of Physical Education and Sport, 16(2)*, 522.

Grün, T. V. D., Franke, N., Wolf, D., Witt, N., & Eidloth, A. (2011). A real-time tracking system for football match and training analysis. *Microelectronic Systems: Circuits, Systems and Applications*, 199-212.

Gupta, N., Gupta, S. K., Pathak, R. K., Jain, V., Rashidi, P., & Suri, J. S. (2022). Human activity recognition in artificial intelligence framework: a narrative review. *Artificial intelligence review, 55(6)*, 4755-4808.

Heng, X., Wang, Z., & Wang, J. (2016). Human activity recognition based on transformed accelerometer data from a mobile phone. *International Journal of Communication Systems, 29(13)*, 1981-1991.

Izzo, R., Febo, M., Cruciani, A., Cejudo, A., & Crudelini, E. (2023)a. Analysis of peak linear accelerations expressed in the technical gesture of gyaku-zuki in Karate/Kumite, comparing dominant and non-dominant limbs, including a complete review of the subject. *Journal of Physical Education and Sport, 23(7)*, 1829-1845.

Izzo, R., Giardi, L., Cejudo, A., Cruciani, A., Giovannelli, M., & Varde'i, C. H. (2023)b. Examining key components in table tennis performance involves analyzing accelerations in elbow and wrist rotations through a physical assessment of technical gestures utilizing inertial sensors an exploratory approach. J*ournal of Physical Education and Sport, 23(11)*, 2883-2890.

Khan, A. M., Lee, Y. K., Lee, S. Y., & Kim, T. S. (2010). Human activity recognition via an accelerometer-enabled-smartphone using kernel discriminant analysis. In 2010 *5th international conference on future information technology* (pp. 1-6). IEEE.

Kojić, F., Mandić, D., Pelemiš, V., & Đurić, S. (2021). Relationship between the 30-second burpee test variation and anthropometric and motor dimensions in female university students. *Kinesiologia Slovenica, 27(1)*, 21-34.

Kos, A., Wei, Y., Tomažič, S., & Umek, A. (2018). The role of science and technology in sport. *Procedia Computer Science, 129*, 489-495.

Kulsoom, F., Narejo, S., Mehmood, Z., Chaudhry, H. N., Butt, A., & Bashir, A. K. (2022). A review of machine learning-based human activity recognition for diverse applications. *Neural Computing and Applications, 34(21)*, 18289-18324.

Mali, N. P., & Dey, S. K. (2020). Modern technology and sports performance: An overview. I*nternational Journal of Physiology, 5(1),* 212-216.

Masagca, R. C. (2024). Comparison of low -intensity steady state training versus high-intensity interval training on key health-related physical fitness components. *Journal of Physical Education and Sport, 24(3)*, 488 – 498.

Mayr Ojeda, E., Castro, F. A. D. S., Reich, M., Astorino, T. A., & Benítez-Flores, S. (2022). Burpee Interval Training Is Associated With a More Favorable Affective Valence and Psychological Response Than Traditional High Intensity Exercise. *Perceptual and Motor Skills, 129(3)*, 767-786.

Moura, F. C. D., Machado, A. A. N., Vieira, L. L., Abreu, E. S. D., Soares, P. M., Brito, G. A. D. C., ... & Costa, E. E. (2016). Jiu-jitsu athletes' cardiovascular responses in an adapted burpee test. *Asian Journal of Science and Technology, 7(1)*, pp.2208-2212.

Ng, J. Y., Zhang, J. H., Hui, S. S., Jiang, G., Yau, F., Cheng, J., & Ha, A. S. (2024). Development of a multi-wear-site, deep learning-based physical activity intensity classification algorithm using raw acceleration data. *Plos one, 19(3)*, e0299295.

Perez-Ifran, P., Magallanes, C. A., Castro, F. A. D. S., Astorino, T. A., & Benítez-Flores, S. (2022). Extremely Low-Volume Burpee Interval Training Equivalent to 8 Minutes Per Session Improves Vertical Jump Compared with Sprint Interval Training in Real-World Circumstances. *The Journal of Strength & Conditioning Research*, 10-1519.

Pernek, I., Kurillo, G., Stiglic, G., & Bajcsy, R. (2015). Recognizing the intensity of strength training exercises with wearable sensors. *Journal of biomedical informatics, 58*, 145-155.

Pierratos, T., & Polatoglou, H. M. (2020). Utilizing the phyphox app for measuring kinematics variables with a smartphone. *Physics Education, 55(2)*, 025019.

Polevoy, G. G. (2023). The influence of Burpee on the volume of attention of schoolchildren. *Bangladesh Journal of Medical Science, 22(2)*.

Podstawski, R., Kasietczuk, B., Boraczyński, T., Boraczyński, M., & Choszcz, D. (2013). Relationship between BMI and endurance-strength abilities assessed by the 3 minute burpee test. *International Journal of Sports Science, 3(1)*, 28-35.

Podstawski, R., Żurek, P., Clark, C., Laukkanen, J., Markowski, P., & Gronek, P. (2019). A multi-factorial assessment of the 3-Minute Burpee Test. *Journal of Physical Education and Sport, 19(2)*, 1083-1091.

Sahin, H. M. (2014). Relationships between acceleration, agility, and jumping ability in female volleyball players. *European Journal of Experimental Biology, 4(1)*, 303-308.

Sahlan, I., & Fayanto, S. (2019). Theoretical and experimental studies on centripetal acceleration using the Phyphox application. *International Journal of Scientific and Research Publications, 9(9)*, 167-171.

Siska, L., & Brodani, J. (2017). Use of burpees in combat sports conditioning training–A Pilot Study. *Int. J. Sports Phys. Educ, 3*, 1-6.

Šiška, Ľ., Hubinák, A., Krška, P., & Broďáni, J. (2020). Development of specific training load in boxing. *Journal of Physical Education and Sport, 20(5)*, 2580-2585.

Tai, J. Q. J., Wong, S. F., Chow, S. K. M., Choo, D. H. W., Choo, H. C., Sahrom, S., & Aziz, A. R. (2022). Assessing physical fitness of athletes in a confined environment during prolonged self-isolation: potential usefulness of the test of maximal number of burpees performed in 3 minutes. *International Journal of Environmental Research and Public Health, 19(10)*, 5928.

Wang, J. R., & Parameswaran, N. (2004). Survey of sports video analysis: research issues and applications. *In Proceedings of the Pan-Sydney area workshop on Visual information processing* (pp. 87-90).