

*Citation for published version:*

Nodari, S, Lopomo, N & Preatoni, E 2019, Automatic classification of functional fitness activities via wearable technology. in *Proceedings of the 25th Conference of the European Society of Biomechanics (ESB 2019)*. European Society of Biomechanics, Vienna, Austria, 7/07/19.

*Publication date:*  
2019

*Document Version*  
Peer reviewed version

[Link to publication](#)

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# AUTOMATIC CLASSIFICATION OF FUNCTIONAL FITNESS ACTIVITIES VIA WEARABLE TECHNOLOGY

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## Introduction

Classifying and recognising human actions play a key role in human-computer interface, daily activity monitoring and estimation of sports performance [1-3]. With these aims, wearable technologies, such as inertial measurement units, have been increasingly used in sports applications due to their low cost and obtrusiveness [3,4]. Yet, the automatic recognition and classification of human actions remains a non-trivial task due to the high complexity of motion data and high intra and inter-individual variability [5]. The aim of this study was to develop and validate a specific to automatically recognise and classify common functional fitness activities.

## Methods

The study included 14 healthy-fit subjects (age 18-50), with >6 months experience in performing functional training. Each participant was asked to wear 5 wireless inertia measurement units (Trigno Avanti, Delsys) and to perform a continuous sequence of 4 popular functional training drills (i.e. Clean and Jerk, Box Jump, American Swing and Burpee). The sensors were placed on the left wrist, upper arm, thigh, ankle and on the lumbar spine, allowing the natural execution of the movement and avoiding any discomfort (Figure 1).



Figure 1: Setup used for the acquisition of the functional training drills. Red circles highlight sensors positions.

Accelerations and angular velocities were sampled at 2000 Hz and synchronized with a video-camera (50 Hz) to allow the visual labelling of each movement. Raw data were segmented by using a fixed-width sliding window of 600 ms with 10% overlap. Feature extraction was both in the time and frequency domains and applied to on each window. Movement classification was implemented by using a supervised approach. Several

classifiers were tested to identify the one the returned the best classification performance. Validation was performed using 5-fold cross test.

## Results

The best classification performances was obtained through a Support Vector Machine (SVM) classifier with cubic kernel (Table 1).

|                | Clean & Jerk | Box Jump    | American Swing | Burpee      | Transition   |
|----------------|--------------|-------------|----------------|-------------|--------------|
| Clean & Jerk   | 93<br>(233)  | 0           | 0              | 0           | 7<br>(17)    |
| Box Jump       | 0            | 81<br>(107) | 0              | 0           | 19<br>(25)   |
| American Swing | 0            | 0           | 88<br>(92)     | 0           | 12<br>(13)   |
| Burpee         | 0            | 0           | 0              | 94<br>(135) | 6<br>(8)     |
| Transition     | <1<br>(5)    | <1<br>(7)   | <1<br>(8)      | <1<br>(3)   | 99<br>(3211) |

Table 1: Confusion matrix showing classification performance in % (count) of the total. TP=true positives; FN=false negatives. Transition= movement phases between repetitions of a movement or different movements.

## Discussion

SVM and k-Nearest Neighbours reported the best performances. The analysis of confusion matrixes showed that the method is able to correctly assign movement windows to each of the four movements. Misclassifications are between 1% (transition) and 19% (box jump) of the total and typically relate to single movement windows erroneously labelled as transition between tasks. The proposed solution was able to classify functional training from inertial sensors, with performance similar to equivalent approaches in different sporting(?) scenarios [1-3]. These findings show good potential towards the development of automatic monitoring systems based on commercially available sensors (e.g. smart watches/wristband, smartphones), which could support the coaching and judging of complex strength and conditioning workouts.

## References

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