PREDICTING ACTIVE FOOT CONTACT IN THE ACCELERATION PHASE OF ATHLETIC SPRINTING THROUGH ACCELEROMETER MEASUREMENTS

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Active foot contact (absence of a braking impulse) during the acceleration phase of athletic sprinting is associated with the motion of the foot before touchdown (TD). Since the identification of braking impulses through force plate measurements is cost-expensive, the aim of this study was to develop a machine learning algorithm to predict active foot contact occurrences based on ankle-mounted accelerometer measurements. Ten recreationally active athletes (three females, seven males) performed 30 sprint-block-starts each, which were used as input to the machine learning model. Model performance was assessed by the AUC for both validation (AUC = 0.96) and testing (AUC = 0.94). It is therefore possible to predict active foot contact occurrence by a machine learning algorithm solely based on ankle-mounted accelerometer measurement data.

KEYWORDS: BRAKING, MACHINE LEARNING, SUPPORT VECTOR MACHINES.

INTRODUCTION: The horizontal acceleration of the body's center of mass (CoM) during the sprint start and early acceleration phase is important for overall sport performance in athletic sprinting (Čoh et al., 1998). Acceleration is determined by the horizontal net impulse produced during the stance phase. Since the horizontal net impulse in running direction equals the sum of posteriorly (braking) and anteriorly (propulsion) directed impulses, athletes can either try to increase propulsion or minimize braking (or a combination of both). Elite sprinters have even shown to be able to avoid braking impulses during the first ground contacts after block clearance. Braking impulses are believed to be a function of touchdown distance and touchdown velocity of the foot (Bezodis et al., 2019). The term touchdown distance refers to the position of the foot in the sagittal plane relative to the vertical projection of the CoM whereas touchdown velocity refers to the velocity of the foot shortly before ground contact. Following this explanation, the foot should be placed slightly behind the vertical projection of the CoM onto the ground (Bezodis et al., 2015) and the horizontal velocity of the foot in running direction should be small or even pointing posteriorly (Hay, 1994) to produce a high propulsive impulse. The existence of a braking impulse and its magnitude during a ground contact in sprinting can be easily derived from force plate signals (gold standard). However, the use of force plates in athletic training requires expensive equipment and building operations and skilled operators raising the need for a cheaper and more user-friendly alternative.
Therefore, the aim of this study is to evaluate whether it is possible to predict the existence of a braking impulse with machine learning by training the model with data from ankle-mounted accelerometer measurements.

METHODS: Three recreationally active female athletes (25.3 ± 2.1 years, 1.7 ± 0.1 m, 64.7 ± 9.5 kg) and seven male athletes (25.4 ± 2.6 years, 1.8 ± 0.1 m, 78.6 ± 8.9 kg) participated in this study. After an individual warm up all participants performed 30 sprint-block-starts and maximally accelerated for 5 m. Ground reaction forces (GRF) (2000 Hz, 600x900mm, Kistler, Winterthur, CH) and the acceleration of the ankle (2000 Hz, dual-axial, operating range: ± 50 g, *i*MEMS®ADXL278 ANALOG Devices, Inc. Wilmington, MA) were sampled simultaneously using the Qualysis Track Manager (Qualysis Inc., Gothenborg, Sweden). The accelerometer was attached to the lateral malleolus of the ankle joint by aligning the vertical axis of the accelerometer with the vertical axis of the lower leg while the athlete was standing (Gruber et al., 2014). The collected data were filtered with a fourth order low-pass Butterworth filter at a cutoff frequency of 50 Hz (GRF) and 20 Hz (accelerometer),

respectively. For each trial the accelerometer data were cut according to the time period of interest which was defined as the time span from initiation of the swing phase (SW; threshold: 0.5 ms^{-2} in anterior direction) of the rear leg until first TD of the foot. The TD was detected by searching for the first peak of the time differentiated vertical acceleration signal with a minimum peak prominence of 70% of the maximum change of acceleration recorded for the whole trial. Both the threshold for the initiation of the swing phase and the peak prominence magnitude for TD detection were determined numerically by evaluating different thresholds with respect to accuracy. The accuracy of the TD detection method was checked against event detection from force recordings (vertical GRF exceeding 20 N) (Aubol and Milner, 2020).
For further analysis the trials were classified into braking (braking force during the first stance phase exceeded 20 N) and no braking. The data were randomly split into training data (n = 237 trials, 83%) and test data (n = 50 trials, 17%). The training data were further analyzed using Matlab's Classification Learner (MATLAB, The Mathworks Inc., Natick, MA, USA). This machine learning approach required pairs of input and corresponding correct output values for training. To prevent overfitting, the model was trained by k-fold cross-validation (k = 5). Once the training was completed, the resulting model could be used for predictions based on test data (data which have not been used for training) (Kim, 2017). As input data to the model, the following characteristics of the acceleration signal (features) have been calculated (see Table 1). The correct output values were obtained from the horizontal GRF by assigning the value 0 to trials without braking (no braking) and the value 1 to trials with an existing braking impulse (braking). Subsequently, the input - correct output pairs were imported into the Classification Learner which trained linear, quadratic, cubic and gaussian support vector machine (SVM) models of which the model resulting in the highest model performance was chosen. Model performance was defined as the area under the ROC curve (AUC) for the validation data (Luo et al., 2016). Furthermore, the test data were used to make predictions and the corresponding test performance (AUC) was compared to the validation performance.

Table 1: Features derived each from the vertical (y) and anterior-posterior (x) components of the accelerometer data with respect to the local coordinate system of the accelerometer.

Feature	Description
Mean acceleration (x,y)	The average acceleration of the foot from SW until TD
Max. acceleration (x,y)	The maximum acceleration of the foot from SW until TD
Min. acceleration (x,y)	The minimum acceleration of the foot from SW until TD
Swing duration	The duration of the swing phase in seconds
Acceleration at TD (x,y)	The acceleration of the foot at initial TD
Acceleration ratio (x,y)	The quotient of the maximum and minimum acceleration of the foot

RESULTS: The initial TD was detected 19 ± 28 ms earlier when compared to the TD obtained from GRF data. The right part of Figure 1 shows the GRF curve in anterior-posterior direction normalized to the stance phase. During the trials classified as braking the subjects produced a mean braking impulse of 1.64 ± 1.12 Ns and a propulsive impulse of 71.30 ± 16.26 Ns, resulting in a net impulse of 69.66 ± 16.43 Ns. The net impulse of the trials classified as no braking amounted to 71.47 ± 13.90 Ns on average. The highest model performance (AUC = 0.96) was reached by a cubic SVM. Subsequently, the trained model (training time: 0.26 s) was used to predict categories from the test data (n = 50) which resulted in correctly classifying 40 out of 50 trials (AUC = 0.94).

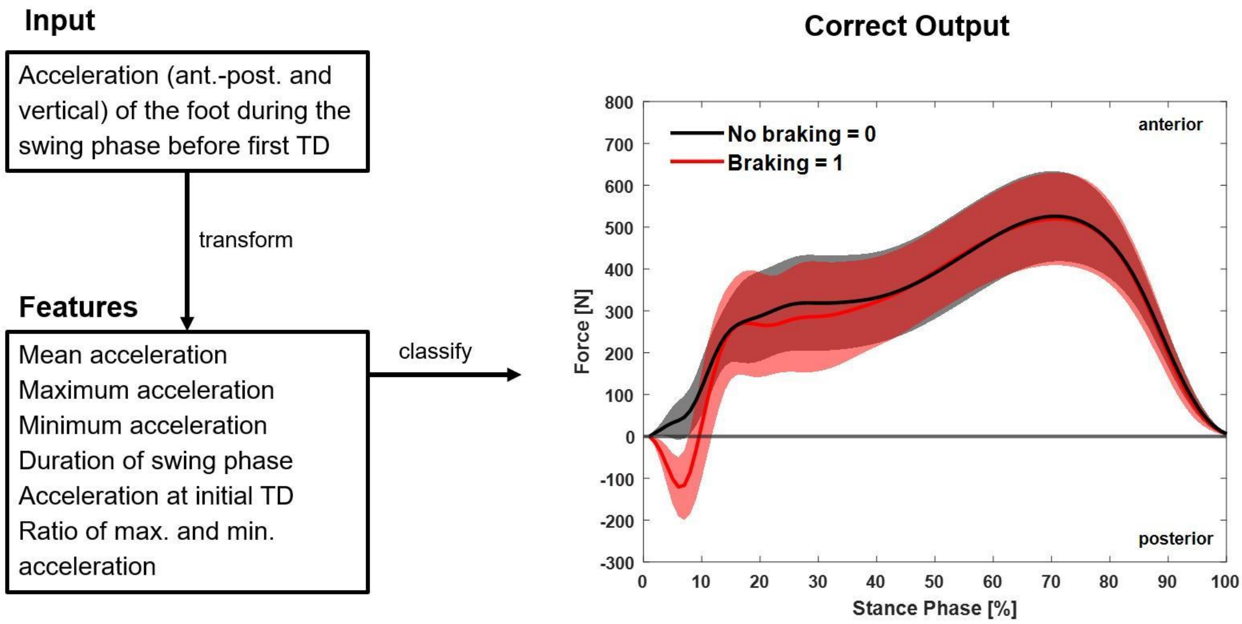

Figure 1: Schematic chart of the machine learning classification process. The model was trained with matching input - correct output pairs. The acceleration of the foot during the swing phase served as input data, which were transformed into features (characteristics of the acceleration signal). The correct output was derived from the GRF of the first stance phase, classified as 0 (no braking, n = 86) and 1 (braking, n = 201).

DISCUSSION: The implemented machine learning algorithm was able to predict active foot contact occurrences during the acceleration phase of athletic sprinting by 88% (based on test data; AUC = 0.94). Assessing the performance of machine learning-based predictive classification tasks by held-out data is a commonly used method (Halilaj et al., 2018). However, comparing the achieved performance in this study with existing literature is somewhat difficult, because the performance is task-dependent and at the time of this study to our best knowledge, there were no data from comparable study designs available. The machine learning algorithm which led to the best performance in this study was a cubic SVM. According to a review article by Halilaj et al. (2018), this algorithm represents the major method used in biomechanical research (approx. 40%).

As real-time feedback of biomechanical parameters is crucial for performance enhancement in elite sports, wearables including embedded data analysis are a suitable tool for online monitoring of movement parameters (Schmidt et al., 2018). Therefore, the implementation of the machine learning algorithm within a wearable would provide athletes and coaches with real-time information about active foot contact occurrence and could potentially contribute to performance enhancement of athletes during sprint starts in terms of fast feedback. Consequently, this would be a cheaper and more user-friendly alternative compared to expensive feedback equipment and skilled operators. Furthermore, research incorporating such a machine learning algorithm-based wearable is not limited to laboratory settings but can be conducted in real-life scenarios (training and competition) and makes time- and cost-intensive post-processing obsolete.

As explained in the methods section, machine learning models require input data in the form of features (in this case characteristics of the acceleration signal). The choice of features in this study was based on trial and error and was very sensitive to the overall performance of the model. More sophisticated, systematic methods of feature extraction such as fast Fourier transforms (Ahlrichs et al., 2016), hidden Markov models (Mannini et al., 2016) or wavelet decomposition (Nielsen et al., 2011) might yield superior results. Another challenge was the detection of the initial foot contact after the start, which was needed to determine the end of the swing phase of the leg of interest. The detection of the foot contact by searching for the

highest change of acceleration of the foot resulted in a deviation of 19 ± 28 ms on average when checking against GRF data. A pattern recognition algorithm based on a machine learning approach itself might further improve the accuracy of TD detection.
Additionally, the relatively small sample size of ten athletes may have limited the performance of the model. Increasing sample size and the collected trials per subject could provide a higher performance level. However, the majority of studies using machine learning in biomechanics investigate sample sizes up to 10 participants (Halilaj et al., 2018).

CONCLUSION: Based on the underlying performance result (AUC = 0.94), a cubic SVM algorithm seems to be a promising alternative to predict active foot contact occurrence (absence of a braking impulse) during the acceleration phase of athletic sprinting. More sophisticated, systematic methods of feature extraction, a more precise TD detection algorithm and a higher sample size might further improve the prediction accuracy of active foot contact occurrence.

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