Development Of Smart Shin Guards For Soccer Performance Analysis Based On MEMS Accelerometers, Machine Learning, And GNSS

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Abstract

The performance analysis of a soccer team has become an important topic for soccer coaches. Parameters like the number of shots, passes or sprints during a match provides information about the game quality. However, currently available systems are based on cost-expensive video analysis, which requires a pre-installed infrastructure. Consequently, such systems are only open to professional teams. The use of low-cost wearables represents an alternative to make such performance analysis accessible to hobby teams.

This paper focuses on the evaluation of different Machine Learning (ML) approaches for the classification of simple, soccer-specific activities (such as standing, walking, running, passing and shooting) based on Micro-Electro-Mechanical Systems (MEMS) accelerometers. To do so, the sensors are mounted on the soccer player's shin guards. Diverse ML algorithms as well as different dimensionality reduction algorithms are investigated. The best approach shows a macro-precision score of 97% and a macro-recall score of 96%.

The final goal is to develop smart shin guards, which can georeference soccer-specific activities in conjunction with sports statistics. The positioning system is based on Global Navigation Satellite Systems (GNSS). This scientific study is part of the Austrian Space Applications Programme (ASAP) 15 and funded by the Federal Ministry of Transport, Innovation and Technology via the Austrian Research Promotion Agency (FFG).

Keywords

Soccer, Activity Recognition, MEMS Accelerometer, GNSS, Georeferencing

1. Introduction

Observing the activities of each soccer player in a match is a big challenge for coaches. For instance, the number of passes, shots, sprints done by the players as well as their positions on the field represent a valued information for the team. The evaluation of those parameters can be used to improve existing strategies or develop new ones that may derive a benefit concerning the team. However, currently available systems are based on video analysis. *skills.lab* [1], founded by Anton Paar SportsTec GmbH (Wundschuh, AUSTRIA), for example, developed such an interactive high-tech training system

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Table 1
List of selected activities, their corresponding abbreviations and definitions [3].

Activity	Abbreviation	Definition
Standing	ST	Being in an upright position with both feet on the ground.
Walking	WA	Moving on foot at moderate speed (≈ 5.5 km/h).
Running	RU	Moving on foot at advanced speed (> 8 km/h).
Pass	PA	Player tries to kick the ball to another teammate.
Shot	SH	A more intense kick.

for soccer players. Specific game situations, utilizing state-of-the-art measurement technologies, can be reproduced to improve the skills of the soccer players [2]. Be that as it may, such systems are associated with a specific infrastructure and high-costs and are thus not affordable for hobby teams in the long term [3].

Commercial wearables are cost-effective to observe the activity and fitness of persons. Smart gadgets, such as smartwatches, are gaining popularity; the number of wearables sold is expected to be around 630 million worldwide until 2024 [4]. Such smart gadgets can contain Global Navigation Satellite System (GNSS) sensors, inertial sensors and heart rate monitors, to name a few [3]. Real Madrid already uses wearables during training sessions for performance analysis [5]. Each player is equipped with a Global Positioning System (GPS) device that outputs parameters like routes, distances, speed, and so on [5]. The collected data is analyzed to gain information on the players' fitness levels. A smart shin guard has already been developed by *soccerment* (Milan, ITALY). This smart gadget comprises inertial sensors in combination with Artificial Intelligence (AI) and a GPS sensor to analyze the soccer player's game quality [6]. The growing importance of soccer performance analysis is obvious. Hence, the development of commercial wearables in the soccer sector shows a big market potential.

This paper deals with the first development steps and examinations of smart shin guards for soccer players. GNSS-sensors are utilized to get the player's position on the field. Micro-Electro-Mechanical Systems (MEMS) accelerometers with Machine Learning (ML) methodologies are used for activity recognition. The result is a georeferenced activity that enables performance analysis. The focus will be on evaluating different ML approaches for the classification of simple, soccer-specified activities. The activities and their definition are listed in Table 1. Among other things, the concept concerning the GNSS-based positioning system will be shown.

In total, four different ML algorithms are investigated: Logistic Regression, Support Vector Machine (SVM), Random Forest Classifier and an Artificial Neural Network (ANN) in form of a Multilayer Perceptron (MLP). Features are chosen in the time- and wavelet-domain. Furthermore, it has been examined, whether the Principal Component Analysis (PCA) or the Linear Discriminant Analysis (LDA) in the meaning of dimensionality reduction algorithms can improve the classification process or not.

2. Related Works

Triaxial accelerometers are popular sensors for activity recognition (AR). The authors of [7] constructed a neural classifier based on accelerometer measurements that is capable of recognizing everyday activities like walking, running, sitting and so on (overall accuracy 95%). Studies like [8, 9] had shown that wavelet-based features from IMU data can be successfully used to detect daily activities such as walking. SoccerMate [10] represents a soccer attribute profiler that uses wrist-worn accelerometer sensor to detect soccer-specific events like passing, shots, walking, running, standing and dribbling (overall accuracy 86.5%). From those events the overall game quality of the soccer player is derived. The authors utilized deep learning methods. Schuldhaus et al. [11] proposed a SVM-based classification scheme to detect passes and shots of soccer player. Therefore, inertial sensors were hidden in the shoe's hollow. This study achieved an overall mean classification rate of 84.2% (60-minute match, 12 players).

3. Test Setup

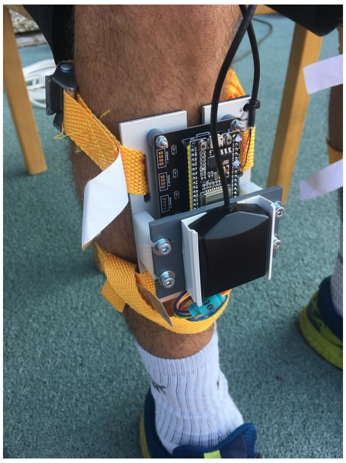
The MPU9250 MotionTracking device [12], produced by *InvenSense Inc.*, is chosen as the embedded Inertial Measurement Unit (IMU). The MPU-9250 consists of triaxial acceleromters, a triaxial gyroscopes and a triaxial magnetometer. This sensor is based on MEMS technology. However, in this study only the accelerometer data is used for AR. The range of the accelerometer is set to its maximum, namely ± 16 g (1 g $\approx$ 9.807 m/s^2 at latitude of Graz). The output rate was set to 100 Hz.

The generation of the GNSS position of the soccer player is done via the Neo-M8T chip from *u-blox*. This chip supports the raw data output so that a position, using an own software, can be calculated. For the first investigations, two u-blox evaluation kits (left and right shin guard) are used. The appropriate antennas are still under investigations for this use case. Therefore, the antennas from u-blox are utilized, which are included in the evaluation kits. The GNSS data recording was done with a notebook in the backpack of the player. With these two raw GNSS data sets, a combined Multi-GNSS position with an update rate of 1 Hz can be calculated.

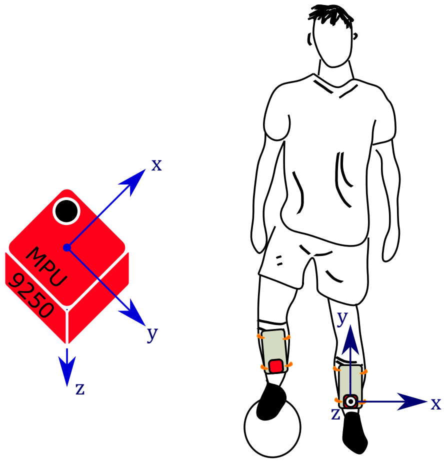
The provisional test setup, including the sensor orientation of the IMU, is shown in Figure 1. Each shin guard will be finally equipped with one IMU, one GNSS chip, one GNSS antenna and the necessary processor units. The IMU is mounted at the lower end of the shin guard to sense the motion performed during a kick as well as possible. The two IMUs are synchronized based on the Precision Time Protocol (PTP). The communication between the two IMUs takes place via Wi-Fi. In this first approach, the recorded accelerometer data is stored on an SD card.

4. Data Collection and Preparation

Before the data collection started, the MEMS accelerometer was calibrated. In the calibration process the bias and scale factor of each axis are determined. The accelerometer



(a) Hardware Components. Photograph by Stefan Laller.



(b) Sensor Orientation (IMU). Sketch by Karin Mascher [3].

Figure 1: Test Setup.

data was recorded from the left and right foot, respectively. Each defined activity (cf. Table 1) was written in a separate log-file on the SD card. *Walking* was done at an average speed of 5.5 km/h. *Running* was performed at three different speeds: 8 km/h, 12 km/h and 17 km/h. The samples for the class *pass* consist of single passes performed with different techniques (inside foot and outside foot) and from different distances (10 m and 20 m). *Passes* were also recorded during running. *Shots* were done with inside foot, outside foot and full instep. Care was taken that the kicks were performed using the right leg as well as the left leg [3].

For segmentation, a window size W of 256 samples (2.56 s) was chosen. *Standing*, *walking* and *running* were segmented with an overlapping window with the size W and an overlap of 50 %. Kicks were cut out so that the acceleration peak is in the center of the window W. Labels were manually assigned [3]. The collected training set is only based on one person. Future studies will provide a sufficiently large sample of human test subjects. In total, 1109 samples are generated (ST: 20.7 %, WA: 11.1 %, RU: 43.8 %, PA: 19.4 %, SH: 5.0 %). Quintic spline functions are fitted to the data for smoothing [13, 3].

5. Methods

This section deals with concept of the AR strategy. Based on the labeled data, different ML approaches have been investigated, which will be explained in more detail below. Computations were done in *Python 3.7* using the ML modules *scikit-learn* and *TensorFlow2* as well as the wavelet transform software *PyWavelets 1.1.1*.

Table 2
Frequency ranges corresponding to different decomposition levels. The sampling rate is 100 Hz.

		Frequency range	[Hz]
Coefficients arrays	**Scale indexing**	**to**	**from**
cD_1	$m = 1$	50	25
cD_2	$m = 2$	25	12.5
cD_3	$m = 3$	12.5	6.3
cD_4	$m = 4$	6.3	3.1
cD_5	$m = 5$	3.1	1.6
cD_6	$m = 6$	1.6	0.8
cD_7	$m = 7$	0.8	0.4
cA_7	-	0.4	0

5.1. Wavelet Analysis

Features are also chosen in the wavelet-domain. Therefore, the Discrete Wavelet Transform (DWT) is utilized as a filter bank. The implementation of the DWT as a filter bank can be seen as a cascade of high-pass (signal details) and low-pass (smoothing effect) filters [14]. The signal is decomposed into so-called approximation and detail coefficients, which corresponds to different sub-frequency bands. The result is a list of coefficients arrays [15]: approximation coefficients array (cA_M) and the detail coefficients arrays ($\text{cD}_M, \ldots, \text{cD}_1$) ($M \geq 0$ refers to the maximum level of decomposition). Depending on the chosen wavelet, the maximum level of decomposition varies. However, the frequency ranges corresponding to different decomposition levels for this special case are listed in Table 2 [3].

The usage of the DWT gives a compact representation of the energy distribution in frequency- and time-domain [14]. As an example, Figure 2 shows the wavelet analysis of two shot records. The signal is expressed in terms of the total acceleration of the shooting leg. The chosen wavelet is the reverse biorthogonal 3.1 (rbio3.1) wavelet. Similar analysis were performed for the other activities.

5.2. Training and Testing

Figure 3 shows a general overview of the training and testing process. The data is split into a training and test set, where the ratio of the training set to the test set is 0.8 to 0.2. The next step is to compute the features for both sets. The chosen features are topic of Section 5.4. The computed features of the training set are transformed several times. This step includes Feature Scaling (standardization) and the selection of an appropriate feature subset (indicated by the blue-dotted box). The selection of an appropriate feature subset is implemented in three ways:

1. Removing features with **low variance**
2. Removing features with **low variance** followed by **Principal Component Analysis (PCA)**: variance explained $\geq 97.5\%$ (keep 97.5% of the “variability” of the

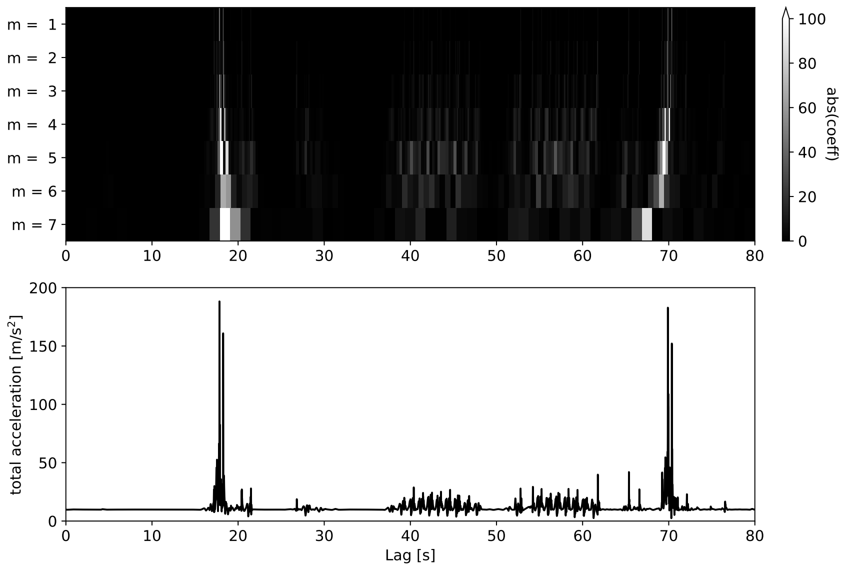


Figure 2: Absolute values of detail coefficients arrays (*abs(coeff)*) of total acceleration of right leg during two shots. Between the two shots the soccer player is walking. Plot from Karin Mascher [3].

original data set) (cf. Section 5.5)

3. Removing features with **low variance** followed by **Linear Discriminant Analysis (LDA)** (cf. Section 5.5)

Those transformation values are applied to the test set.

The box "Machine Learning" pictures the training of the different ML algorithms based on the different feature subsets. In total, four different ML algorithms are investigated:

1. Logistic Regression
2. Support Vector Machine (SVM)
3. Random Forest Classifier
4. Artificial Neural Network (ANN): Multilayer Perceptron (MLP)

The training comprised the selection of the model parameters as well as the hyperparameter tuning. Since the input data is imbalanced, small classes receive respectively stronger weights. 5-fold cross-validation was used for model evaluation (hyper-parameter tuning, feature selection, ...). In a final step, the test set is fed into the trained model. The output are predicted labels that are compared with the actual labels. Hence, an unbiased quality of the ML model can be assessed.

To sum up: the performances of four different ML algorithms that are based on three different feature selection methods are analyzed (12 combinations in total).

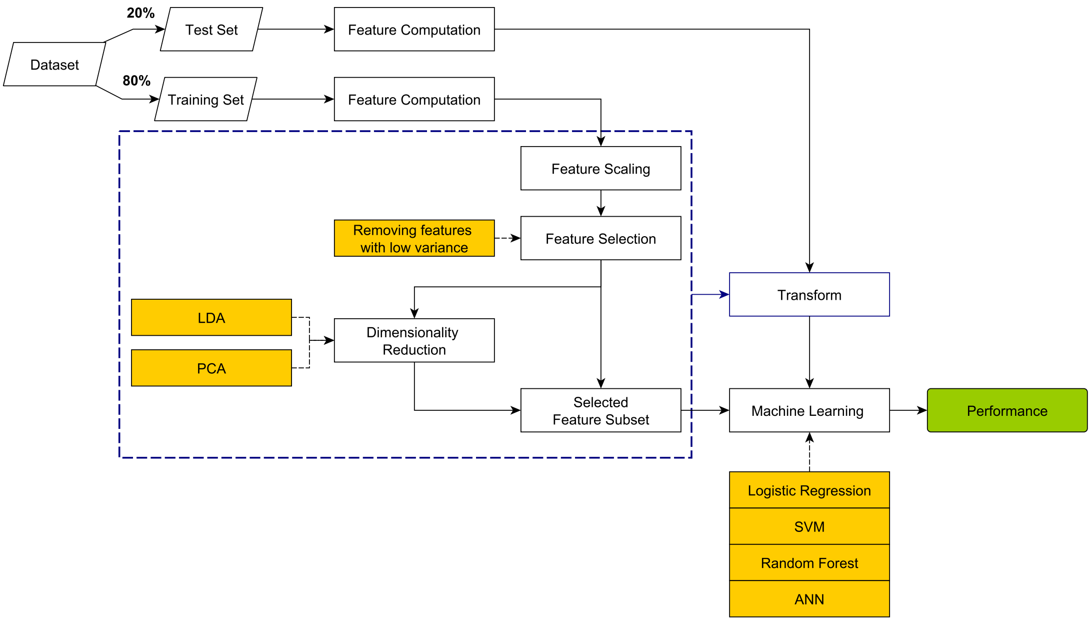


Figure 3: Flowchart of Training and Testing the ML algorithm. Flowchart by Karin Mascher [3].

5.3. Activity Recognition Strategy

The AR strategy is split into two parts [7]: The pre-classification phase tries to separate kicks from standing, walking and running. The second phase assigns the signal to the actual activity that the soccer player performs. Figure 4 shows the flowchart of the AR scheme [3]:

1. **Pre-Classifer Construction (grey boxes):** This phase should separate kicks from the other activities, such as standing, walking and running. The acceleration data from the right leg is subtracted from the data of the left leg [11]. The idea is that a kick causes a high peak in the data. This peak should be visible after the subtraction, while signals from standing, walking and running end up in noise. A binary decision is made: pass or shot are assigned as "1" (positive class), standing, walking and running as "0" (negative class).
2. **Standing/Walking/Running-Classifier Construction (blue boxes):** The model assigns the signal to standing, walking or running.
3. **Pass/Shot-Classifier Construction (red boxes):** Before the Pass/Shot Classifier assigns the signal to a pass or a shot, a processing step is necessary: the detection of the shooting leg. That is achieved by comparing the peaks of the total acceleration of the xz-plane. The y-component has not been considered to avoid erroneous classifications due to deceleration movements (cf. Figure 1b).

Such divisions of the classifiers allow to select the features more individually.

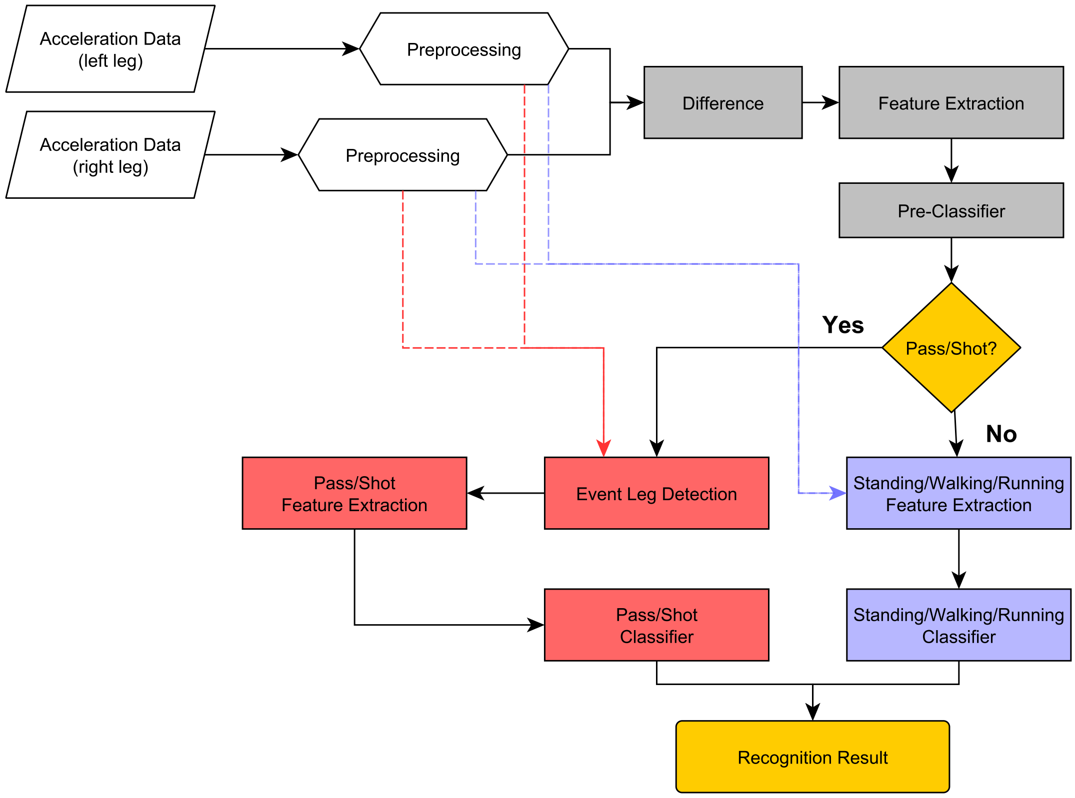


Figure 4: Flowchart of Soccer Activity Recognition. Flowchart by Karin Mascher [3].

5.4. Feature Selection

Features are chosen in the time- and wavelet-domain and for each classifier separately. Wavelet-based features are expressed in the terms that are used in Table 2. The appropriate mother wavelet is visually selected based on the resemblance between the signal of interest and the different wavelet types [9]. The maximum level of decomposition was also taken into account.

5.4.1. Pre-Classifer Construction

The total acceleration $\boldsymbol{a}_{total}$ is calculated as follows

$$a_{\text{total},i} = \sqrt{x_i^2 + y_i^2 + z_i^2}, \tag{1}$$

where i is the i^{th} element of the acceleration vectors $\boldsymbol{x}$, $\boldsymbol{y}$ and $\boldsymbol{z}$ of dimension W. W refers to the window size. The largest and second largest value from $\boldsymbol{a}_{total}$ are selected as features. These features imply the intensity of a kick as well as the corresponding pre- and post-impacts [3].

The Signal Magnitude Area (SMA) (introduced by [7]) of the xz-plane

$$\mathrm{SMA} = \frac{1}{W}\left(\sum_{i=1}^{W} |x_i| + |z_i|\right) \tag{2}$$

as a feature intends to characterize passes and shots since the x- and z-axes are mainly affected during kicks. The maximum of absolute detail coefficients array in each subband (exclusive $\boldsymbol{cD_1}$) gives an indication about the intensity of the activity. This feature is based on the reverse biorthogonal 3.1 (rbio3.1) wavelet. The variability of the activity can be described by the Root Mean Square (RMS) of detail coefficients array in each subband (exclusive $\boldsymbol{cD_1}$):

$$\mathrm{RMS}(cD_j) = \sqrt{\frac{1}{N_j}\sum_{i=1}^{N_j} cD_{j,i}^2}, \tag{3}$$

where $cD_{j,i}$ $(j \in \{2, \ldots, M\})$ is associated with the i^{th} component of the detail coefficients array. N_j is the dimension of the coefficients array at level j and M refers to the maximum level of decomposition. The analysis is based on the rbio3.1 wavelet. $\boldsymbol{cD_1}$ is not considered, since frequencies between 25 Hz to 50 Hz are of no interest to the pre-classification process. The mean and maximum of absolute approximation coefficients array cA_M as well as the RMS provide information about the low frequency components. The mean is obtained using the following formula:

$$\mathrm{MEAN}(cA_M) = \frac{1}{N}\sum_{i=1}^{N} |cA_{M,i}|, \tag{4}$$

where N is the dimension of the approximation coefficients array. The formula for the RMS and maximum are analog to those of the detail coefficients. Here also the rbio3.1 wavelet is used.

5.4.2. Standing/Walking/Running-Classifer Construction

The maximum, the mean (Formula 5) and the Interquartile Range (IQR) (Formula 6) are computed for each sensor axis and chosen as features in the time-domain. The following formulas are illustrated for an arbitrary vector $\boldsymbol{a}$ of dimension W.

$$\mathrm{MEAN}(\boldsymbol{a}) = \frac{1}{W}\sum_{i=1}^{W} a_i, \tag{5}$$

where a_i is the i^{th} element of the vector $\boldsymbol{a}$.

$$\mathrm{IQR}(\boldsymbol{a}) = Q_3(\boldsymbol{a}) - Q_1(\boldsymbol{a}), \tag{6}$$

where $Q_1(\boldsymbol{a})$ is the first quantile and $Q_3(\boldsymbol{a})$ the third quantile of the vector $\boldsymbol{a}$.

The total SMA [7] also serves as a feature:

$$\text{SMA} = \frac{1}{W}\left(\sum_{i=1}^{W} |x_i| + |y_i| + |z_i|\right). \tag{7}$$

Studies [8, 16] had shown that walking is mostly presents in the frequency range from 0.6 Hz to 2.5 Hz. Therefore, the RMS of the detail coefficients arrays of level $j \in \{4, 5, 6\}$ are used as features (0.8 Hz to 6.3 Hz). The frequency range has been extended to also cover well the activity running. As wavelet the daubechies 2 (db2) is chosen. Walking and running mainly have an impact on the signal in the sagittal plane [8]. Therefore, the features are computed from the y and z-component, respectively.

5.4.3. Pass/Shot-Classifer Construction

The two largest values of the total acceleration of the xz-plane are used as a feature.The Pearson correlation coefficient between the total acceleration (Equation 1) of the event and supporting leg is computed and shown in the following formula:

$$r = \frac{\sum_{i=1}^{W}\left(a_{\text{total},i}^{(\text{support})} - \bar{a}_{\text{total}}^{(\text{support})}\right)\left(a_{\text{total},i}^{(\text{event})} - \bar{a}_{\text{total}}^{(\text{event})}\right)}{\sqrt{\sum_{i=1}^{W}\left(a_{\text{total},i}^{(\text{support})} - \bar{a}_{\text{total}}^{(\text{support})}\right)^2}\sqrt{\sum_{i=1}^{W}\left(a_{\text{total},i}^{(\text{event})} - \bar{a}_{\text{total}}^{(\text{event})}\right)^2}}, \tag{8}$$

where $\bar{a}_{\text{total}}^{(\text{event})}$ and $\bar{a}_{\text{total}}^{(\text{support})}$ represent the mean values of the event leg and the supporting leg, respectively. This feature gives information about the activity of the supporting leg. Since during the event of a shot, the supporting leg is more active than during a pass, a correlation between the activity of the right and left leg is given [3]. In the wavelet-domain, the maximum values of the absolute wavelet coefficients are chosen as features. The total acceleration (Equation 1) serves as the input signal. The rbio3.1 wavelet (cf. Figure 2) and the Discrete Meyer (FIR Approximation) (dmey) wavelet are used as wavelets, respectively. Thus, the distinction between passes and shots is defined over the intensity of the kick and the activity of the supporting leg. Analysis of the feature importance had shown that the features computed from the supporting leg are more important that features based on the event leg.

5.5. Dimensionality Reduction Algorithms

Due to the *curse of dimensionality* that says "as the number of variables under consideration increases, the number of possible solutions also increases, but exponentially" (William S. Noble [17, p.1567]), it is challenging for ML algorithms to find an accurate solution. Hence, one solution is to reduce the number of features by projecting the original feature space onto a lower-dimensional one and that with a minimum of information loss [18, 3].

Two dimensionality reduction algorithms are investigated in the course of this study:

Table 3
Total number of features.

Variant	**1**	**2** (PCA)	**3** (LDA)
Pre-Classifier	42	12	1
Standing/Walking/Running-Classifier	32	10	2
Pass/Shot-Classifier	25	13	1

1. **Principal Component Analysis (PCA)**
   PCA is an unsupervised dimensionality reduction algorithm. The algorithm tries to find a hyperplane that preserves the maximum variance of the original. Correlated features are transformed in linearly uncorrelated ones. The new features are named principal components (PCs) [19, 18, 3].
2. **Linear Discriminant Analysis (LDA)**
   LDA is a supervised dimensionality reduction algorithm, which aims to find a hyperplane that keeps the classes as far away as possible. The new features are known as linear discriminants (LDs) [19, 3].

More information about those dimensionality reduction algorithms can be found in [19, 20, 21, 22]. Table 3 now contains the total number of features based on the different feature selection methods.

6. Results

The chosen performance metrics are based on the macro-averages of the precision and recall scores. The macro-average is chosen since this metric is preferred when dealing with imbalanced data sets.

The training and test scores for all models were above 96.9% (precision) and 97.5% (recall). All approaches show potential to correctly classify standing, walking, running, passes and shots. The final models are trained on the whole data set and applied to real, but simple data to find out which model is best able to detect the activities. That data set is composed of five sequences that include the soccer-specific gestures. Each sequence consists of: standing ($\approx$ 1 min), followed by running with increasing speed (8 km/h up to 12 km/h), a short pause and a walking phase ($\approx$ 4 km/h). During the running phase, two passes and one shot is performed. During the walking phase, one pass is done. Figure 5 illustrates the validation set expressed in form of the total acceleration. Kicks are performed with the left and right leg as well as with different techniques (insight foot, outside foot, full instep).

The used window size is 256 samples. The overlap is around 60%. Tables 4 to 6 show the precision and recall scores of the different ML models (Section 5.2).

The best results show Logistic Regression and the Random Forest Classifier used in combination with the Linear Discriminant Analysis (LDA). They are the only models that received perfect precision and recall scores for the classes *pass* and *shot*. Misclassifications only took place in the transition areas between standing, walking and running.

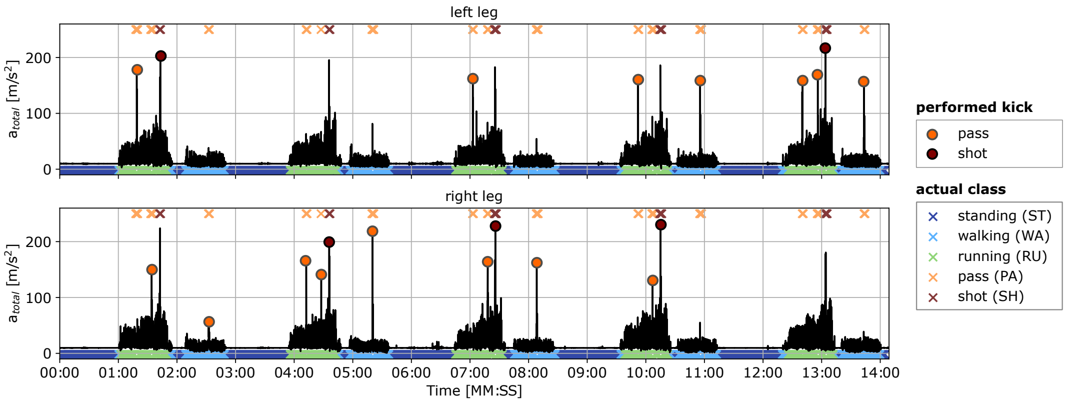


Figure 5: Real data. Crosses refer to the actual classes that are used for comparison with the predicted classes. The dots indicate the performed kicks as well as the shooting leg.

Table 4
Evaluation scores for variant 1.

ML algorithm	Precision [%]	Recall [%]
Logistic Regression	96.5	93.8
SVM	96.3	91.6
Random Forest Classifier	94.7	90.2
ANN	95.5	92.8

Table 5
Evaluation scores for variant 2 (PCA).

ML algorithm	Precision [%]	Recall [%]
Logistic Regression	96.6	94.4
SVM	93.7	90.5
Random Forest Classifier	81.6	72.2
ANN	92.9	88.0

Hence, those errors are not considered as severe ones. The worst performance shows the Random Forest Classifier in combination with the Principal Component Analysis (PCA). The recall score for walking, for example, was only around 50%. Since Decision Tree classifiers use linear and orthogonal decision boundaries, they tend to overfit and do not work well an new instances that are slightly different from the training data. In this special case, the walking phase in the real data set is performed at an average speed of 4 km/h, but the walking instances used for training are done at an average speed of 5.5 km/h.

Table 6
Evaluation scores for variant 3 (LDA).

ML algorithm	Precision [%]	Recall [%]
Logistic Regression	97.4	96.1
SVM	97.0	94.8
Random Forest Classifier	97.4	96.1
ANN	95.2	95.8

7. Conclusion

This study compared different ML models with each other based on a modular classification scheme. The performance was evaluated on real, but simple data to figure out which ML model performs the best. First, the use of two IMUs is a powerful tool to distinguish passes from shots. On the one hand, the intensity of the kick is sensed by the event leg. On the other hand, the activity of supporting leg is higher during a shot than during a pass. Secondly, it has been shown that the Linear Discriminant Analysis (LDA) is well suited for the selection of an appropriate feature subset. LDA significantly outperforms the two other feature selection methods and worked pretty well for all ML algorithms. However, applying the Principal Component Analysis (PCA) to the feature subset does not improve the classification process. Third, the ANN only showed a mediocre performance. One explanation could be that Neural Networks are designed to deal with large data sets. The existing data set is relatively small. Fourth, the sensor exceeded its maximal range of ± 16 g when performing a shot. But it was sufficient to separate passes from shots.

The used data is only based on one test person. Thus, future studies will aim to collect data from a sufficient number of test persons to create a model that can be used for a broader audience. Another goal is to implement more activities in the classification process, such as tackling, dribbling and other more complex gestures. The activities still need to be georeferenced to get a Location-based Service (LBS) that enables an easier performance analysis of soccer players. The concept is shown in the last section of this paper (Section 8).

To sum it up, under laboratory conditions, it is possible to detect simple, soccer specified activities using a MEMS accelerometer. The best performance has been achieved with Logistic Regression and the Random Forest Classifier combined with the Linear Discriminant Analysis (LDA). These models had a macro-precision score of 97.4% and a macro-recall score of 96.1%. They were also able to detect all passes and shots.

8. Outlook: Georeferenced activity

Figure 6 shows the basic principle of the entire process from data recording to a georeferenced activity.

The upper part of the diagram shows the principle of the combined GNSS positioning.

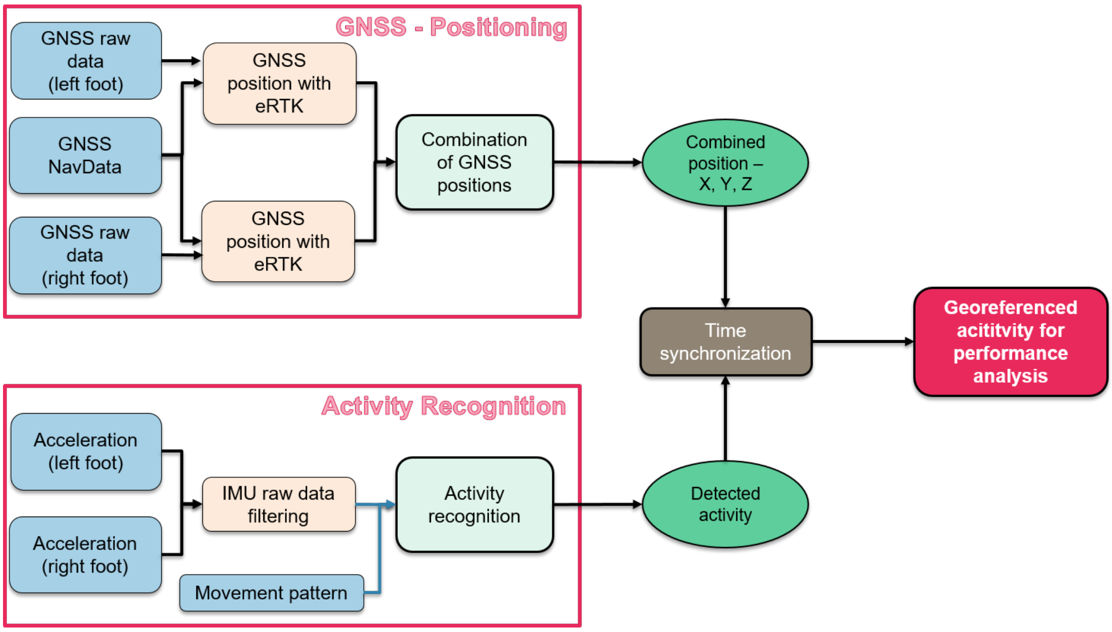


Figure 6: Strategy for georeferencing the activities.

For the processing of the GNSS raw data the software "eRTK" from the Institute of Geodesy (Working Group Navigation) is used. This software uses GPS and GALILEO observations for the determination of a Multi-GNSS Single Point Positioning (SPP). The positions from both shin guards are combined with an algorithm, which weights the positions with the covariance matrix from the least-squares adjustment [23]. The idea for using Multi-Receiver and Multi-GNSS is that a more robust position can be calculated. The verification of the position solution is done by high-priced GNSS equipment.
In a further step, the time synchronization of the position and the detected activity is done. Due to the GPS timestamp of the player's position and a Coordinated Universal Time (UTC) timestamp of the activity, this task can be done easily. The result is a georeferenced activity for performance analysis of soccer player.

Further investigations will show which accuracy and availability can be achieved with this setup. Furthermore, it has to be investigated if the whole concept can be used in a real soccer game and can be used for performance analysis of soccer players.

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