Inertial Sensor-Based Approach for Shot/Pass Classification During a Soccer Match

Dominik Schuldhaus[1], Constantin Zwick[2], Harald Körger[2], Eva Dorschky[1], Robert Kirk[2], Bjoern M. Eskofier[1]
[1] Digital Sports Group, Pattern Recognition Lab,
Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Germany
{dominik.schuldhaus, eva.dorschky, bjoern.eskofier}@fau.de
[2] adidas AG, Herzogenaurach, Germany
{constantin.zwick, harald.koerger, bob.kirk}@adidas.com

ABSTRACT
Coaches and players in soccer are heavily interested in statistics like number of shots and passes during training sessions and competitions. Currently available systems use video or computerized technology to create such statistics and are therefore mainly applicable for elite teams. Thus, the purpose of this paper was to develop a low-cost inertial sensor-based approach for shot/pass classification in soccer, which can be used by teams at amateur level. High intensity peaks were detected in the accelerometer data from the left and right shoe of soccer players. Segmented windows around the peaks were classified regarding shot, pass, and other. The system was evaluated based on data from 12 players during a 60-minute soccer match. The system was able to differentiate between shots and passes with an overall mean classification rate of 84.2 %. The proposed approach is one important step toward a detailed soccer match analysis system, which provides coaches and players of amateur teams with important statistics for performance assessment.

1. INTRODUCTION
Nowadays, non-invasive sensor systems are able to monitor physiological functions, daily activities, and individual behaviors. Different application areas exist, ranging from health monitoring [3] to performance assessment in sports [2]. One goal, which is important in both areas, is the detection and classification of certain events in sensor signals. In [3], a system was proposed which classified heartbeats to either normal or four abnormal beats. Features based on electrocardiogram morphology, heartbeat intervals, and RR-intervals were extracted. A statistical classifier model was applied using supervised learning. The proposed approach reached a sensitivity of 75.9 %.
In [2], a single inertial-magnetic measurement unit was attached to a tennis player's forearm during a competitive match. A threshold-based technique was used to detect strokes based on the accelerometer data, and a sensor fusion approach using accelerometer, gyroscope, and magnetometer data was applied to classify serves, forehands, and backhands. The proposed approach achieved an overall stroke classification rate of 90 %.
Apart from health monitoring and individual sports like tennis, event detection and classification are also important in team sports, e.g. soccer. Information about events like number of passes, crosses, and shots in training sessions and competitions is essential to provide coaches and players with a detailed performance assessment.
In [6], the performance indicators in soccer were identified that discriminated winning teams from drawing, and losing teams in the UEFA Champions League. It was shown that winning teams had significantly higher average values regarding e.g. total shots ($p < 0.01$) and passes ($p < 0.05$). Currently available systems use video or computerized technology to create such statistics, and are therefore mainly applicable for elite teams due to high costs and low portability of the equipment [1]. There is a major need for providing amateur teams in soccer with low-cost and portable solutions for the detection and classification of certain events, e.g. passes and shots. Inertial sensors are successfully applied for event analysis in sports like tennis [2].
To the best of the authors' knowledge, the applicability of a low-cost inertial sensor-based approach for shot/pass classification in soccer as an alternative to expensive computerized systems was not yet examined in the literature. State-of-the-art approaches used in health monitoring and individual sports are hardly applicable. Compared to the detection of heartbeats, which are periodic, events like passes and shots do not regularly appear during soccer matches. Inter-event features like the RR-interval are not applicable [3]. Algorithms which are based on thresholds like for the detection of tennis strokes [2] are not applicable due to the highly dynamic and complex motions of players during soccer matches. Furthermore, in individual sports, opponents does not influence the behavior of the athlete like in soccer, in which e.g. tackling actions are performed.
Thus, the purpose of this paper was to develop a low-cost inertial sensor-based approach for shot/pass classification in soccer.
The developed system can be one important step toward a detailed soccer match analysis system providing coaches and

KDD Workshop on Large-Scale Sports Analytics 2015, Sydney, Australia
.

players of amateur teams with important statistics which can be used for performance assessment.

2. MATERIALS AND METHODS

2.1 Data Acquisition

The hardware consisted of a custom-made system comprising of a sensor and storage unit. The sensor unit included an inertial measurement unit (IMU) in order to acquire movement data of the lower extremities of soccer players. The IMU was placed in a cavity of a soccer shoe (Figure 1a) and consisted of a triaxial accelerometer and a triaxial gyroscope with a range of ± 16 g and ± 2000 $^\circ/s$, respectively. The sampling rate was set to 1000 Hz.
The storage unit was located in the shin guard (Figure 1b). Sensor unit and storage unit were connected by cable. One system was used for each leg. Thus, 12 sensor axes were recorded.
Two studies were conducted, in which inertial sensor data of passes and shots were acquired. Video data was used as gold standard for labeling in both studies.
In the first study, eleven male players (age 29.6 $\pm$ 9.2 years, height 182.3 $\pm$ 6.3 cm, weight 77.7 $\pm$ 9.8 kg) performed a protocol including different controlled exercises. The exercises were divided into two groups.

The first group of exercises consisted of single passes and shots. In the case of passes, three distances (4 m, 9 m, and 15 m) between a teammate and the subject were chosen in order to have different intensities of passes. For each distance, eight continuous passes were performed without controlling the ball. For each distance, the exercise was separately performed with the left and right leg. In the case of shots, the subject had to shot three times at the goal. This procedure was performed with the left and right leg.
The second group of exercises consisted of combinations of passes and shots with more complex actions, e.g. dribbling, control, tackling, slalom, and running. Passes and shots had to be performed with the preferred leg.

All in all, each subject had to perform 64 passes and 12 shots.
In a second study, 17 male players (age 29.6 $\pm$ 6.6 years, height 182.3 $\pm$ 6.4 cm, weight 80.6 $\pm$ 9.2 kg) were equipped with the sensor and storage unit. These players participated in an 11 vs. 11 game. The game had a duration of around 60 minutes with a four minute break. Only one player, who participated in the first study, was involved in the second study. One player got injured and was removed from the database. For four players, inertial sensor data for both shoes were not available, e.g. due to sensor problems during the game. Since the proposed algorithm required inertial sensor data for both shoes, these players were removed from the database.

(a) Sensor unit placed in soccer shoe.

(b) Storage unit placed in shin guard.

Figure 1: Hardware setup.

2.2 Peak Detection

In the following sections, the four steps of the proposed algorithm are described, which detected and classified passes and shots from inertial sensor data.
The first step was to detect peaks in the accelerometer data, which represented candidates of passes and shots (Figure 2a). A Butterworth high-pass filter was applied to the inertial sensor data of both legs in order to remove low frequency movements like walking. The signal magnitude vector (SMV) of the high-pass filtered inertial sensor data was computed for both legs, in order to get the intensity of movement [5] and to remove the direction of movement. The computation of the SMV signal was performed by summing up the squared amplitudes of all three axes of the accelerometer at each sample point and extracting the root. The SMV signals of both legs were subtracted and only the absolute amplitudes of the resulting difference signal were considered for the peak detection (Figure 2b). It was assumed that during the execution of a pass and a shot, the signal intensity of the event leg was higher than the signal intensity of the supporting leg. Computing the absolute difference had the advantage that peaks of events from both legs were visible in one signal. The local peaks in the absolute difference signal above a certain threshold were detected and ranked in descending order of the amplitudes. In Figure 2b, the threshold is indicated by the red line and the detected peaks are indicated by the red circles.
Peaks, which were present 1s before and after a detected, higher-ranked peak, were removed, since it was assumed that no additional event can occur during this period.

2.3 Segmentation

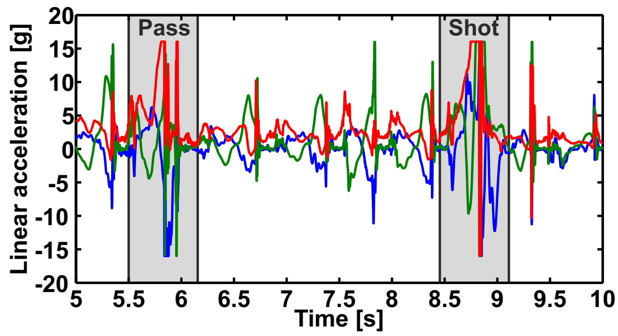
The second step was to segment the inertial sensor data. Therefore, a window W centered around each detected peak was defined. The window size of 1s was chosen, which was the maximal duration of a shot.

2.4 Event Leg Classification

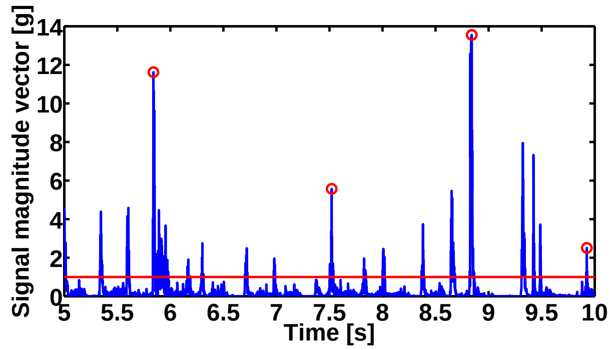
The third step was to classify the leg which performed the event. A classification system C_{Leg} was established, which mapped a segmented window W, containing the raw sensor signals, to the two classes $\{LEFT, RIGHT\}$. If W was classified as $LEFT$, $LEFT$ was defined as event leg, and $RIGHT$ was defined as supporting leg, and vice versa. By classifying the event leg in an early step of the system, the distinction of the cases, in which the event was performed with the left or right leg was not needed. C_{Leg} consisted of two parts.

- Feature extraction: four statistical features (mean, variance, skewness, and kurtosis) were extracted for each of the twelve sensor axes. Statistical features are among others heavily used in activity recognition [7]. This resulted in 48 features in total.

- Classification: three different classifiers were trained based on the extracted features. In detail, Support



(a) Linear acceleration of right shoe.



(b) Absolute difference signal of SMV signals (blue), threshold (red line), and peaks considered for segmentation (red points).

Figure 2: Illustration of peak detection for exercise 'dribbling - pass - running without ball - shot'.

Vector Machine (SVM, linear kernel), Classification and Regression Tree (CART), and Naive Bayes (NB) were compared [8].

2.5 Event Classification

The fourth step was to classify the segmented windows regarding the events shot and pass, and an additional class denoted as "other". "Other" included e.g. actions like tackling, fast running, and side steps. For the event classification, a hierarchical approach was developed consisting of two classification systems. The first classification system C_{Oth} was established, which mapped a segmented window W, containing the raw sensor signals, to the two classes $EVENT$ and $OTHER$. In the $EVENT$ class, shot and pass instances were merged. The classification system consisted of the same steps as C_{Leg}. The second classification system C_{Ev} further subdivided the segmented windows W, which were classified as $EVENT$ by C_{Oth}. The output classes of C_{Ev} were denoted as $PASS$ and $SHOT$. The classification system consisted of the same steps as C_{Leg} and C_{Oth}.

2.6 Performance Assessment

The performance assessment was divided into two parts. The number of instances that were available are given in Table 1. The instances were labeled based on the video data. In the first part of the performance assessment, the single systems C_{Leg}, C_{Oth}, and C_{Ev} were evaluated independently from each other. For C_{Leg}, all instances of passes and shots with the corresponding labels $\{LEFT, RIGHT\}$ were

	Study 1	Study 2
PASS	884	336
SHOT	181	18
OTHER	771	3581

Table 1: Number of instances of passes, shots, and "other" available for first study (protocol of exercises) and second study (game).

	SVM	CART	NB
C_{Leg}	99.9	99.1	98.5
C_{Oth}	96.7	92.5	91.8
C_{Ev}	88.6	86.1	87.1

Table 2: Evaluation of single systems event leg classification C_{Leg} and event classification C_{Oth}/C_{Ev} based on first study; mean classification rates in percent are given.

used. For C_{Oth}, all instances of passes, shots, and "other" with the labels $\{EVENT, OTHER\}$ were used. In order to get "other" instances, the peak detection algorithm and the segmentation were applied to the inertial sensor data. The segmented windows which, according to the video data, did not correspond to passes or shots were assigned to the "other" class. For C_{Ev}, all instances of passes and shots with the corresponding labels $\{PASS, SHOT\}$ were used. In the first part of the performance assessment, all subjects of the first study were included. In order to evaluate the performance of SVM, CART, and NB regarding the three systems C_{Leg}, C_{Oth}, and C_{Ev}, the mean classification rates were computed with a leave-one-subject-out cross-validation (LOSO-CV). During each LOSO-CV trial, the cost parameter C of the SVM was optimized by grid search with $C \in \{0.01, 0.1, 1, 10, 100\}$. The best classifiers determined for C_{Leg}, C_{Oth}, and C_{Ev} were trained and used for building up the complete system.
In the second part of the performance assessment, the complete system from peak detection to event classification was evaluated. Twelve subjects of the second study were included. Since sensor data from both shoes were needed for the proposed approach, five subjects had to be excluded. This part of the performance assessment was not used for training of the system, only for testing the complete system. The performance assessment focused on the evaluation of the event classification. For the evaluation, the mean class-dependent classification rates and the overall mean classification rates were computed for C_{Oth} and C_{Ev} separately [4]. For the evaluation of C_{Ev}, only those instances of $PASS$ and $SHOT$ were considered which successfully passed C_{Oth}.

3. RESULTS

In the following paragraph, the results of the first part of the performance assessment are given. The mean classification rates for C_{Leg}, C_{Oth}, and C_{Ev} can be seen in Table 2. The best classifier was SVM in all three cases with a classification rate of 99.9 %, 96.7 %, and 88.6 % for C_{Leg}, C_{Oth}, and C_{Ev}, respectively.
In the following paragraph, the results of the second part of the performance assessment are given. The classification system C_{Oth} reached a mean classification rate of 82.8 % and 96.2 % for $EVENT$ and $OTHER$, respectively. The

	EVENT	OTHER
EVENT	**293**	136
OTHER	61	**3445**

Table 3: Evaluation of C_{Oth} based on second study; confusion matrix is given; columns represent the actual classes, rows the predicted classes.

	PASS	SHOT
PASS	**227**	2
SHOT	51	**13**

Table 4: Evaluation of C_{Ev} based on second study; confusion matrix is given; columns represent the actual classes, rows the predicted classes.

overall mean classification rate was 89.5 %. The confusion matrix of C_{Oth} can be seen in Table 3. The classification system C_{Ev} reached a mean class-dependent classification rate of 81.7 % and 86.7 % for passes and shots, respectively. The overall mean classification rate was 84.2 %. The confusion matrix of C_{Ev} can be seen in Table 4.

4. DISCUSSION

In the following paragraph, the results of the first part of the performance assessment are discussed. The achieved classification rates showed that the single systems were suitable to determine event leg (C_{Leg}), additional actions like tackling, jogging, ... (C_{Oth}), and the considered events pass and shot (C_{Ev}). The performance might be further improved by using additional features, e.g. in the frequency domain such as spectral centroid or bandwidth.

In the following paragraph, the results of the second part of the performance assessment are discussed. Regarding C_{Oth}, 293 events were correctly classified as events (Table 3), resulting in a mean classification rate of 82.8 % for $EVENT$. Nevertheless, 61 events were falsely classified as OTHER. The reason might be that the execution of the events in the game was very different compared to the execution in the training phase of C_{Oth}, which consisted of inertial sensor data from exercises. In order to increase the performance, online learning in combination with an individual system for each player might be a solution. The resulting mean classification rate of 96.2 % for $OTHER$ indicated that the proposed system can remove most of the "other" instances like tackling or jogging. The falsely detected events might come from high intensity movements during the game with a duration equal to the window length. An improvement might be choosing a larger window and modeling not only the event but also the actions before the event.

Regarding C_{Ev}, 51 instances of passes were falsely classified as shots and two instances of shots were falsely classified as passes (Table 4). The reason for the misclassifications might be that during matches a clear execution of a pass or a shot was not performed compared to the execution in the first study (protocol of exercises). In order to further improve the performance, additional sensor positions could be used, e.g. shank or ankle, and a larger study should provide more instances of shots and passes for the training phase of the system.

All in all, overall mean classification rates of 89.5 % and 84.2 % were achieved for C_{Oth} and C_{Ev}, respectively. The results showed that a low-cost inertial sensor-based event detection and classification of passes and shots in soccer are in general possible. The generic structure of the system offers the possibility to adapt the algorithms to other events, e.g. crosses or tackling actions.

5. SUMMARY AND OUTLOOK

In soccer, the performance assessment like number of passes and shots is mainly performed by expensive video and computerized technology and thus can be mainly applied by elite teams. There is a major need for providing amateur teams with low-cost and portable solutions. State-of-the-art algorithms available in health monitoring and individual sports can hardly be applied in soccer. Thus, the purpose of this paper was to develop a low-cost inertial sensor-based shot/pass classification system for soccer teams at amateur level, mainly consisting peak detection, segmentation, event leg classification, and event classification. The system was able to differentiate between shots and passes with an overall mean classification rate of 84.2 %. The proposed approach can be seen as one necessary step toward a detailed sensor-based match analysis system for amateur teams. Coaches can use the statistics of the system to setup the optimal team for the next match.

6. ACKNOWLEDGMENTS

This work was supported by the Bavarian Ministry for Economic Affairs, Infrastructure, Transport and Technology and the European fund for regional development.

7. REFERENCES

[1] C. Carling, T. Reilly, and A. M. Williams. *Performance Assessment for Field Sports*. Routledge, London, UK, 2009.

[2] D. Connaghan, P. Kelly, N. E. O'Connor, M. Gaffney, M. Walsh, and C. O'Mathuna. Multi-Sensor Classification of Tennis Strokes. *IEEE Sens J*, pages 1437–1440, 2011.

[3] P. de Chazal, M. O'Dwyer, and R. B. Reilly. Automatic Classification of Heartbeats Using ECG Morphology and Heartbeat Interval Features. *IEEE Trans Biomed Eng*, 51:1196–1206, 2004.

[4] T. Fawcett. An introduction to ROC analysis. *Pattern Recogn Lett*, 27(8):861–874, 2006.

[5] D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell, and B. G. Celler. Implementation of a Real-Time Human Movement Classifier Using a Triaxial Accelerometer for Ambulatory Monitoring. *IEEE Trans Inf Technol Biomed*, 10(1):156–167, 2006.

[6] C. Lago-Penas, J. Lago-Ballesteros, and E. Rey. Differences in performance indicators between winning and losing teams in the UEFA Champions League. *J Hum Kinet*, 27:135–146, 2011.

[7] O. D. Lara and M. A. Labrador. A Survey on Human Activity Recognition using Wearable Sensors. *IEEE Commun Surv Tut*, 15(3):1192–1209, 2013.

[8] S. Theodoridis and K. Koutroumbas. *Pattern Recognition (4th Edition)*. Academic Press, San Diego, CA, USA, 2008.