Using Wrist-Worn Activity Recognition for Basketball Game Analysis

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ABSTRACT

Game play in the sport of basketball tends to combine highly dynamic phases in which the teams strategically move across the field, with specific actions made by individual players. Analysis of basketball games usually focuses on the locations of players at particular points in the game, whereas the capture of what actions the players were performing remains underrepresented. In this paper, we present an approach that allows to monitor players' actions during a game, such as dribbling, shooting, blocking, or passing, with wrist-worn inertial sensors. In a feasibility study, inertial data from a sensor worn on the wrist were recorded during training and game sessions from three players. We illustrate that common features and classifiers are able to recognize short actions, with overall accuracy performances around 83.6% (k-Nearest-Neighbor) and 87.5% (Random Forest). Some actions, such as jump shots, performed well (± 95% accuracy), whereas some types of dribbling achieving low (± 44%) recall.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**; • **Computing methodologies → Machine learning**; **Feature selection**; *Cross-validation*;

KEYWORDS

activity recognition, wearable sports analysis, wrist-worn IMU sensors, basketball action detection

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Figure 1: A basketball player while dribbling and shooting (top), the raw inertial sensor data (middle plot) with classified sequences (bottom plot).

1 INTRODUCTION

Monitoring sports activities is a well-known field of application for human activity recognition systems, with a large number of possible use cases for recognizing and analyzing sport activities. In this paper, we introduce an approach for recognizing different kinds of activities for basketball specifically, from wrist-worn inertial sensor data. For this purpose, data has been collected during the training of a local amateur team from three participants using an Inertial Measurement Unit (IMU) sensor.

We annotated the gathered IMU data in five particularly challenging classes: low dribbling (ld), crossover (co), high dribbling (hd), jump shot (js) and a void class for less relevant actions, and used a supervised learning approach to examine how distinctive these motion classes are. With further development, our aim is to recognize more activities like passing and screening or player movements so that such detectors can reconstruct, visualize or analyze crucial actions that appear during a basketball game.

2 RELATED WORK

Many studies that were carried out in the last years have shown that traditional machine learning methods are absolutely capable of fulfilling the requirements for well-selected activity recognition tasks. The following will discuss activity recognition approaches that were presented for sports activities in particular.

Scientific work in which wearable sensors were used to record motion data in sports is available for many sports. These include swimming [1], table tennis [2], skateboarding [5], ski jumping [6], running [7], home exercises [8], cricket [9], climbing [10], basketball [13], dressage [17], tennis [19], football [20] as well as activities of daily-living [4].

Though due to further developments of wearable technologies we are now able to gather data from many sensors only by wearing just a single gadget. As a consequences, nowadays, researchers are meeting these challenges by using data from wearable sensors for supervising movements. For example [13] developed a new sensor system, which is equipped with IMU sensors to record acceleration, gyroscope, temperature, magnetometer and barometer data. These boards are placed on the lower back, legs, and feet. The recorded data are used to categorize activities in eight different, basketball related, classes. Jog (1), Walk (2), Jumpshot (3), Layupshot (4), Pivot (5), Jumping (6), Running (7), Sprint (8).

In addition to IMU data, others are also using environmental data like temperature or humidity and physiological signals, like heart rate or blood pressure to recognize a variety of sport activities. For instance [12] recognizes eight different activities: cycling (1), training at the cross trainer (2), rowing (3), running (4), squatting (5), stepping (6), walking (7) and weight lifting (8). Another related work is [11], where sport, as well as daily activities are classified by using an unsupervised machine learning algorithm and data from smart-phone accelerometers.

In [16], a basketball game is divided into five key activities: player movement (1), dribbling action (2), pass (3), screen (4), and shot (5). For this the players wore a GPS-tracker and got filmed while playing. Both GPS and video data were used, which were then combined for a time-motion and video analysis. The results are visualized with an own approach. The authors of [15] introduced a system for fine-grained activity recognition in Baseball videos from YouTube that is capable to analyze the video data and categorize the player movements into eight different actions: Ball (1), Strike (2), Swing (3), Hit (4), Foul (5), In Play (6), Bunt (7) and Hit by Pitch (8). They compared four different aggregation methods for video analysis and classified the resulting frame segments into one of the eight classes. [18] have evaluated hip versus wrist worn IMU sensors for seven activity classes, were one of the recognized classes was playing Basketball. They pointed out that wrist worn sensors are working slightly better for recognizing Basketball with an overall accuracy of 86% versus 81.9%. In [14], the authors have proposed a trajectory-based approach for recognizing multiplayer behavior in basketball games by first segmenting the game data into three phases: offense play, defense play and time-outs. Afterwards, a detailed analyses is performed by using video tracked, player-specific data. A Gaussian Mixture Model was used to classify the data into three classes: starting formation (1), move (2) and screen (3). With this data they are able to evaluate the personal personal performance of each player.

3 SYSTEM DESIGN

The two system components used in our approach are (1) a sensor system that is worn around the wrist, and (2) the classification approach that estimates the basketball actions from the streaming sensor data. Although such system could consist of an off-the-shelf smartwatch, we developed our system on a custom prototype to have full control of the embedded sensing system and access to the raw IMU data.

Hardware

The bulk of the computing power, power management, and wireless communication modules is provided by this off-the-shelf board, which is produced by Intel Corporation. The EDI2.SPON.AL.S version of the module, which we use for the Platypus, is CE and FCC certified and specifically made for wearable devices. The module's main processor is a 22 nm Intel Atom "Tangier" (Z34XX) that includes two Atom Silvermont cores running at 500 MHz and one Intel Quark core at 100 MHz (for executing RTOS ViperOS). The system has 1 GB RAM integrated on package. There is also 4 GB eMMC flash storage on board, with Wi-Fi, Bluetooth 4 and USB controllers. Its dimensions are 35.5 x 25 x 3.9 mm.

The Edison module runs an embedded version of the Linux operating system, Yocto, which is an open source collaboration project that provides templates, tools and methods to help create custom Linux-based systems for embedded products, regardless of the specific hardware architecture. All sensors are populated on an Edison-compatible printed circuit board that contains several sensors that immediately interface to the Edison's microprocessors. Additionally, a battery gauge and recharging circuit is added, as well as a miniature display connector for a Sharp Memory LCD. This collection of peripheral modules is directly interfaced to the Edison board via its miniature 70-pin connector. The board has furthermore been extended to contain optical pulse oximeters or sensors for measuring skin conductivity, as separate modules attached to the custom sensor PCB. The prototype is

Figure 2: The wrist-worn sensor prototype we use in our system is specifically designed to capture, pre-process, and classify all data locally. It is equipped with an energy-efficient display, a full IMU, 5 environmental sensors, a dual-core processor at 500 mHz, and a microcontroller running at 100 Hz. Its runs embedded Linux, and can be accessed via Bluetooth 4.0 and WiFi modules.

powered from an off-the-shelf 3.7V, 600 mAh Lithium-Ion rechargeable battery of similar dimensions.

The display is a 1.28 inch (32.51mm) 128 x 128 pixel Monochrome HR-TFT Transflective LCD Panel produced by Sharp, which is especially energy-saving when infrequently updated. It has a viewing area of 23.04mm x 23.04mm and a dot pitch of 0.18mm x 0.18mm. The most important sensor for this paper is the MPU-9250 (by Invensense), which includes a 3D accelerometer, 3D gyroscope, and a 3D magnetometer, in order to capture motion and orientation as accurately as possible. Figure 2 shows the whole prototype, enclosed in a custom-built case with a transparent top part, so that the light sensors can still capture ambient light conditions and the display remains visible, without requiring holes.

Classification Approach

This subsection investigates the nature of the recorded raw data, the structures of the feature vectors and the methods used in the field of machine learning.

A first visual inspection shows through example data records for the data to be classified. As an example, typical patterns for low dribbling is the constant frequency of particular peaks that occur at shorter intervals in time than in the classes crossover and high dribbling, see Figure 3. High dribbling, as depicted in Figure 4, can be characterized by a strongly increasing acceleration, which remains at a high level for about half a second, rather than dropping rapidly again. A crossover movement can be recognized by the fact that there is a gap of about 2 - 3 seconds between two dribblings, as seen in Figure 5. The reason for this is that player carries the sensor at the dominant hand, but the ball is dribbled with the other hand for a short time, thus the

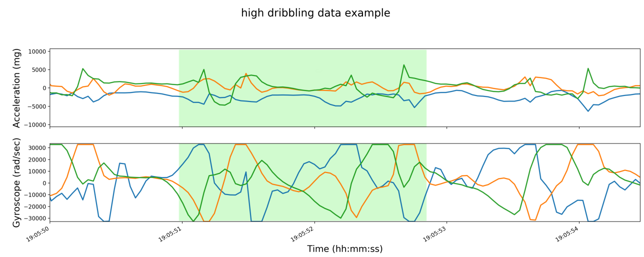

Figure 3: Typical time series for the high dribbling motion, showing the acceleration in milli-g and gyroscope data in rad/sec over time. Clear patterns can be seen in both acceleration and gyroscope data, but for further analysis we will focus on accelerometer data.

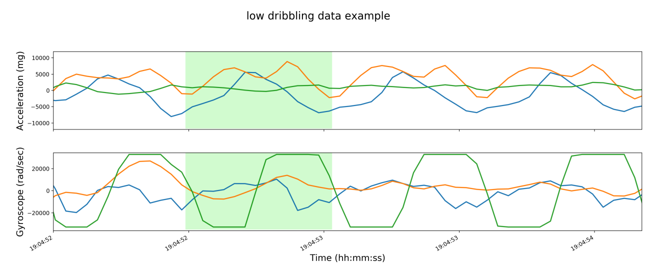

Figure 4: Typical time series for the low dribbling motion, showing the acceleration in milli-g and gyroscope data in rad/sec over time. Faster and more high-speed patterns can be seen in both the acceleration and gyroscope data.

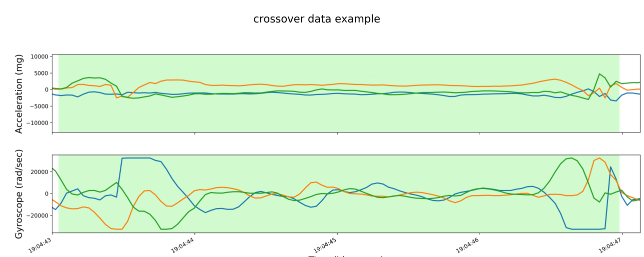

Figure 5: Time series example for a crossover motion, showing the acceleration in milli-g and gyroscope data in rad/sec over time. .

acceleration on the dominant hand decreases sharply for a short period of time. In Figure 6 one can see the recorded data as recorded for a jump shot. Significant for this class are consecutive peaks followed by a major drop of aprox. 10000 milli-g back to 0 milli-g in the acceleration. Due to the dropping acceleration of the z-axis (blue line), the first peak can be interpreted as dribbling followed by a jump shot.

Based on the data we used sliding windows with a window size of one second that got classified by our algorithm. This window size has been chosen, because basketball is a very fast sport with rapidly changing activities. Therefore one activity mostly is in the range of milliseconds to one second. Features has been calculated for every window. For feature extraction only are the acceleration data used. At the first step the, data from the gyroscope, magnetometer,

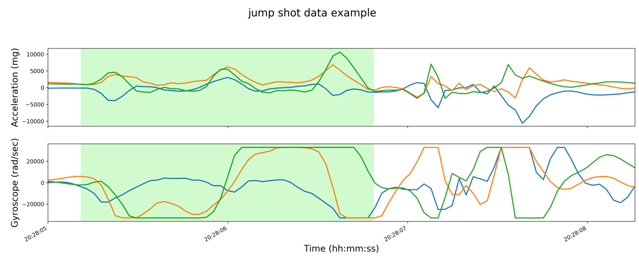

Figure 6: Typical time series for a jump shot, showing the acceleration in milli-g and gyroscsope data in rad/sec over time. Clear patterns can be seen in both acceleration and gyroscope data. In the first version of our System gyroscope data are not taken into account.

environmental sensors, or the battery status are not taken into account by the algorithm. The used features are the arithmetic mean and the standard deviation for every axis of the acceleration data. This allows us to work with a 6-dimensional feature vector.

In our first approach we used a supervised learning method and focused on three different kinds of dribbling as well as jump shots. In the experiment a small data set for training that contains six seconds of data per class and per participant is used. To train the model, we used 150 data sets per participant and per class, i.e. a total of 2225 data sets. The sampling rate at which the data has been recorded is 25Hz.

To optimize the classification results and to improve comparability, classification has been done with a k-Nearest-Neighbor as well as a Random Forest classifier. Both from the scikit-learn package and implemented in Python. For parameter optimization of the individual classifiers, we ran the cross-validation experiments mentioned in the following section for parameters over several ranges to obtain the optimal choices as listed in Table 1.

Table 1: Best-performing parameters per classifier.

k-Nearest-Neighbor	Random Forest
n_neighbors: 4	n_estimators: 10
weights: distance	max_features: auto
algorithm: kd_tree	max_depth: None
leaf_size: 10	min_sample_split: 2
p: 1	min_sample_leaf: 1
metric: minkowski	bootstrap: True

4 EVALUATION

In this section, the followed methodology is described in more detail and a first evaluation of the results is presented.

Methodology

Three participants were recruited for a user study. The participants are between 26 and 31 years old, none of them female, and all of them experienced basketball players. Participants

Table 2: The accuracy, precision, and recall performance in percent for all classes: fast dribbling (fd), crossover (co), high dribbling (hd), jump shot (js), and background data (void).

	k-Nearest-Neighbor				
class	**ld**	**co**	**hd**	**js**	**void**
accuracy	76.5	81.4	81.0	94.5	87.7
precision	43.2	57.7	51.8	85.5	67.7
recall	56.0	27.0	58.4	87.6	74.2
	Random Forest				
class	**ld**	**co**	**hd**	**js**	**void**
accuracy	83.5	83.0	82.4	96.6	91.9
precision	62.4	56.3	55.5	89.6	82.0
recall	44.2	67.8	61.5	94.2	76.0

wore the sensor, which was started approximately half an hour before the practice, on their dominant hands and were briefed on the purpose of the study before the recording.

From participant 1 30 minutes or about 45000 data points were recorded, whereas from both other participants 2 and 3, one hour or about 90000 data points were recorded, summing up to an approximately 235000 data points in total. For later annotation of the data, the participants were filmed during the game. With the additional time-based information from the video material, we are able to identify specific sequences in the data and annotate them with the correct label. With the labeled data we trained the model with a supervised method in combination with leave-one-out cross-validation. To avoid an imbalance of the model, we decided to limit the number of training data per class to 450 examples. To determine the accuracy, precision and recall for each class and classifiers, their values were calculated for each iteration step of the leave-one-user-out cross-validation and finally the average across all folds was formed.

Results

The results, as depicted in the Figures 7 and 8, as well as the determined accuracy, precision and recall in table 2 shows that it is possible to achieve an average accuracy of 87.6% even with few training data and simple features. The confusion matrices 7 and 8 show that the classes low dribbling and high dribbling are slightly better recognized than crossover. Above-average recognizable are jump shots. The recognition of this class is already possible with an accuracy of 96,6%. Due to the good accuracy, but fluctuating precision, it can be stated that the values of the features formed vary greatly, but the classification is nevertheless largely correct. This suggests that in the further course of research, the annotation of the training data must be carefully examined again and, if necessary, improved. Both classifiers vary in their results in terms of precision and recall. This leads to the conclusion that in future works more classifiers should be tested with our data. An average accuracy of 87.5% is not yet optimal. This still leaves room for improvement of the system. An extension or refinement of the used features would result in an improvement of the algorithm. The presented application setup shows a novel combination that works well under laboratory conditions and with hardware comparable to the design and comfort of smartwatches.

Discussion

In this section the most related work of [13] is compared to our proposed method. Furthermore the differences, as well as the advantages and disadvantages between both approaches will be discussed. The technical setup of [13] consists of five self-developed boards with installed IMU sensors. The hardware needs be placed on the players body. One needs to be attached at the lower back, and each one on both legs and feet. Those five devices are recording the data independently from each other. The recorded data run through the common known processes of a machine learning application, i.e. preprocessing, segmentation, feature extraction and classification. For recognizing a specific activity a decision tree has been developed. Wherein the first step is to distinguish between a standing and moving activity. Only after a moving activity has been recognized they decide which movement particularly has been executed. Ten features are utilized to calculate the correct class, for every segment of data each accelerometer, in total four values, are obtained and transformed into a feature-vector. The used features are *range, sum, mean, standard deviation, mean crossing rate, skewness, kurtosis, frequency bands, energy* and *number of peaks above a throshold.* The sampling-frequency that is used was first set at 200Hz, but was down-sampled to 40Hz for the accelerometers due to redundant data.

In contrast to this, the approach presented comes with a single IMU worn at the wrist, which is the most active part of the body while playing basketball for the player who currently owns the ball. As a result of this, the focus of our system is set on the direct interaction with the ball. The used features are limited to mean and standard deviation for every axis of the accerelometer. Therefore the setup is held less complex compared to [13]. Both approaches are evaluated with the signals of three participants.

The lower complexity of the experiment is at the same time its greatest advantage. The small number of devices involved results in less redundant data. In addition, the system offers less space for disturbing factors. Furthermore, with only one device that the player has to wear at the body, the system offers better wearing comfort and has less impact on the players performance. As other works already depicted, for example [3], it is also possible to detect walking or running activities by only wearing one wrist placed IMU sensor.

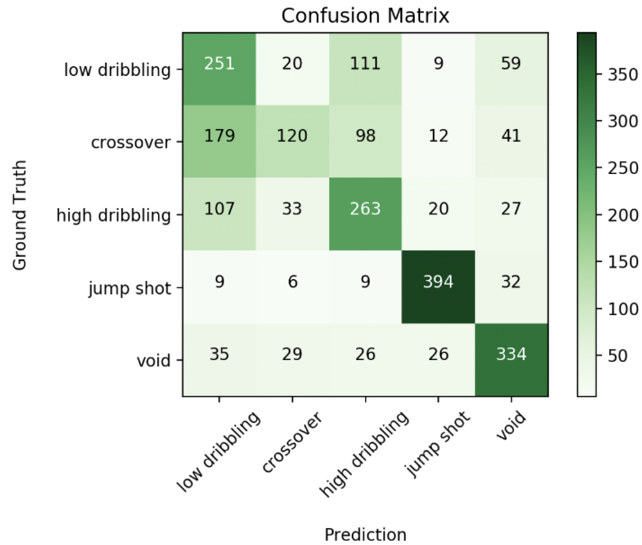

Figure 7: The confusion matrix for kNN shows particular confusion among dribbling, and good results for jump shots.

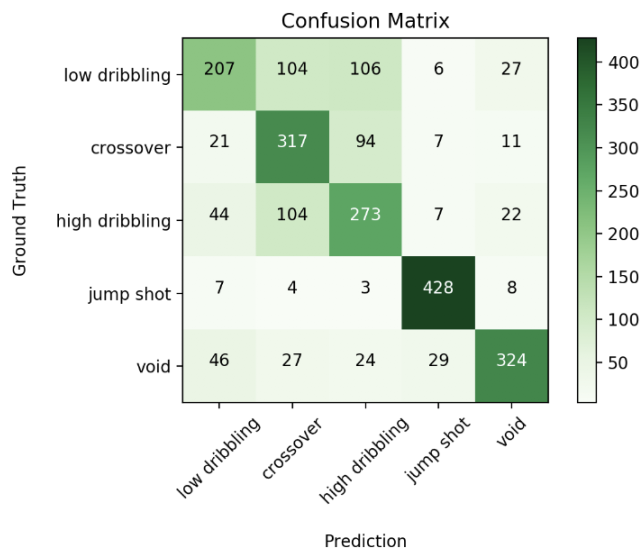

Figure 8: The confusion matrix for Random Forest shows a slightly better per-class performance and equal confusion among the different dribbling actions.

Due to these circumstances we would prefer a test-setup as proposed by us and try to improve it further to be able to classify more activities and improve the accuracy.

5 CONCLUSIONS AND FUTURE DIRECTIONS

We argue in this work that wristwatch-based motion sensors are ideally placed to detect basketball-relevant actions and gestures. The results of this first feasibility study suggest that it is possible to classify different movements of a basketball player using an inertial sensor that is worn on the wrist.

Through this feasibility study, it is now possible to expand the system and add more activity classes. By completing the system and the resulting possibility to recognize all actions of a basketball game only by means of acceleration data, it is possible in the following to recognize the actions of players in real time and without the help of video data annotation. This enables a live analysis system that is able to visually display the recorded games and, in a next step, develop the system for live game analysis.

Furthermore, one could use the system for training purposes and thus design, for example, a feedback system that gives the training player feedback as to whether the action he was currently performing was technically correct. This would be especially useful for shooting training: The board could be equipped with visual feedback reflecting the correctness of the action performed, or offer more detailed action analysis.

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