Goalkeeper Analytics Using a Wearable Embedded System

Bogdan IANCU
The Bucharest University of Economic Studies
bogdan.iancu@ie.ase.ro

The aim of this research is to identify the main metrics linked to soccer goalkeeping that can be computed by using a small embedded device. Based on the identified KPIs, a prototype is created by using an old Android phone in order to compute them based on the values of the three sensors related to positioning: accelerometer, gyroscope and magnetometer. In the final part of this paper, the obtained results are validated in a real case scenario by comparing the values of computed KPIs against some baseline values. The baseline values are extracted from the video recording of the trainings where the goalkeepers used our wearable embedded system. By constructing a cheaper and smaller version of our prototype, we can help small soccer teams to understand and use data to better train their goalkeepers.
Keywords: *sport analytics, embedded system, IoT, wearables*

1 Introduction

Data analysis is not a new research domain. Papers related to different analytics date back to 1865 when Gregor Mendel gathered data about pea plants and the way they pass their traits to their descendants. By creating a small statistical model, he discovered the principles of genetics and how inheritance works [1]. One century and a half later we do not use paper and pencil anymore and we do not limit our data to several characteristics (dimensions). Even though data analysis led us to create a specific department in large businesses (BI – Business Intelligence) and even if we are talking now about Big Data, this paradigm change was not possible in sports until recent years [2]. The main reason was that we did not have developed small enough sensors that can be attached to athletes without affecting their performance. The thing that changed it all was the emerge of IoT (Internet of Things). By using very small sensors that can be easily packed together and attached to athletes (wearables), we can now measure their performance in real time. Industry related data shows that the global sport market values around 1.5 trillion US dollars [3]. The better the team is, the larger the sponsorships and the amount of money received from different associations are. Soccer is considered the king of sports, its annual peak being the UEFA Champions League Final - “The world’s most watched annual sporting event” with more than 165 million viewers [4]. Sometimes the tactics of this sport exceed the perception limits of the soccer managers or coaches, some causalities or important information being buried deep inside the data. With the emerge of wearables, some soccer teams started using GPS devices in trainings to better understand their players’ performance. In 2015 FIFA (the international soccer association) approved for the first time the usage of Electronic Performance and Tracking System (EPTS) devices during matches with the condition to not use the collected data in real time on the technical area [5]. In 2018 they removed this condition just before the World Cup Championship from Russia, the data being used right now by the bench members, by a data analyst and by the team’s medical staff during the game [6].
These EPTS devices are usually GPS-based (exceptions consists of the devices used for indoor arenas which are usually based on a Local Positioning System [7]) and are worn by the players under the jersey in a special pocket created in a compression vest just between the shoulder blades (figure 1). The main producers of EPTS systems are STATSports, Catapult and GPSports [8].

Fig. 1. Players wearing EPTS devices from GPSports. Image source: https://indianexpress.com/article/sports/football/running-hard-but-not-hard-enough/

2 Goalkeeping related KPIs

The goalkeeper is a special position in soccer, his actions being totally different than the ones of a field player. His focus is to catch the ball with his hands as quickly as possible by using different dives and jumps, rather than running quickly and control the ball with his feet. That is why the data collected from an EPTS device worn by a goalkeeper should be interpreted differently. From all the soccer wearables producers enumerated above, just Catapult has a special product dedicated for the goalkeepers: Catapult OptimEye G5 [6].

The Catapult team, according to public available information [9], analyses the following KPIs (Key Performance Indicators) related to goalkeeping:

- Number of left dives versus number of right dives
- Jump height – divided in three categories: low jumps (between 0 and 20 cm), medium jumps (between 20 and 40 cm), high jumps (more than 40 cm)
- Dive return – divided in two categories: medium (between 1 and 1.5 seconds) and high (under 1 second)
- Total running distance – divided in two categories: low intensity and high intensity (at least 5 m/s)
- Maximum speed reached

These KPIs can help teams identify biased behaviour in their goalkeepers' performance, as the case of one of the Bournemouth's goalkeepers who had left to right dive imbalances, aspect that was not observed directly by the coaches [9].

The price of a Catapult OptimEye G5 device is not public, but most probably it is similar to the one of the OptimEye S5 (the field player version) which is around 300 US dollars. This price could be too high for small teams, especially for the teams who play at an amateur level.

With a focus on the KPIs identified by the industry we created a proof-of-concept goalkeeper analysis system based on an old Android phone. Taking into consideration that most Android phones have sensors like accelerometer, gyroscope and magnetometer they could be a good base for testing some hypotheses without spending too much money to create a small, ready-to-use version of our device.

In the testing phase, the Android phone was attached, with its screen facing the exterior, to the left arm of the goalkeeper with an armband as shown in figure 2.

Fig. 2. Goalkeeper wearing the armband with the Android phone attached

3 Android based proof-of-concept

In order to compute the identified KPIs, we developed a custom Android application that uses the phone's internal positioning sensors like accelerometer, gyroscope and magnetometer to identify the dive or jump type and its intensity. Most of the Android devices contain three-axes positioning sensors with the following meanings. Accelerometer measures the phone's acceleration on three axes: X, Y and Z in m/s^2. The Z axis is zero-based and measures positive values if the phone accelerates with the screen towards something and negative values if it accelerates in opposite direction. X axis is also zero-based and has positive values if the phone is moved towards its right margin and negative if it is moved to its left. The Y axis is a special one because at rest it indicates 9.81 m/s^2, the default acceleration due to Earth's gravity. Figure 3 a) shows the accelerometer's distribution of axes on an Android smartphone. On the other side, gyroscope measures phone's rotation against its centre in rad/s, positive values for the axes meaning anticlockwise rotations and negative values, clockwise rotations. The distribution of axes for a gyroscope is presented in figure 3 b). Finally, a magnetometer measures the geomagnetic field strength along the three axes in μT. The axes distribution is similar with the one used by the gyroscope, as shown in figure 3 c). Not all the Android phones have all the three positioning sensors, but this thing can be easily detected programmatically. In fact, the gyroscope can be easily replaced by the magnetometer and vice versa [10]. Additionally, some Android phones have also a special sensor dedicated for counting steps. It was not the case of the phone used by us, but this can be helpful if the GPS sensor could not be used for determining the speed and distance related KPIs (the case of indoor fields).

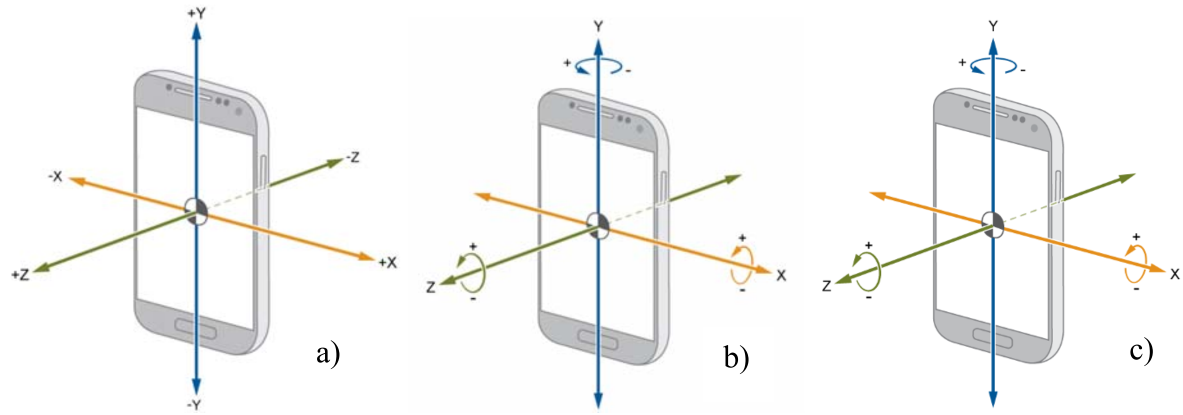

Fig. 3. Distribution of axes for an Android phone: accelerometer (a), gyroscope (b) and magnetometer (c). Image source: https://www.mathworks.com/help/supportpkg/android

The first experiment was to identify left and right dives based on the three sensors presented above. In order to achieve that we used a simple application that logged the sensors' values and we started to simulate different kind of dives. Based on the experiments we found out that the threshold value for the Z axis of the accelerometer is -12 m/s^2 for left dives and around 10 m/s^2 for the right dives. The difference between left and right was caused by the position of the phone (on the goalkeeper's left hand). In order to add more accuracy to the KPI we combined the values given by the magnetometer also, just to be sure that we are measuring a left dive, not a dive return from a right dive for example. The threshold values were 20 µT for left dives and -30 µT for right dives measured on the Z axis. We did not use the gyroscope, even if it would have been more precise for this, because the Android phone that we did the tests on didn't have one. As stated in [10] the magnetometer can replace the gyroscope if none is present, with the remark that any magnetic field from the phone's vicinity will disturb the values, that is why the gyroscope is preferred. The graphs of the sensors' measurements for a left dive are presented in figure 4.

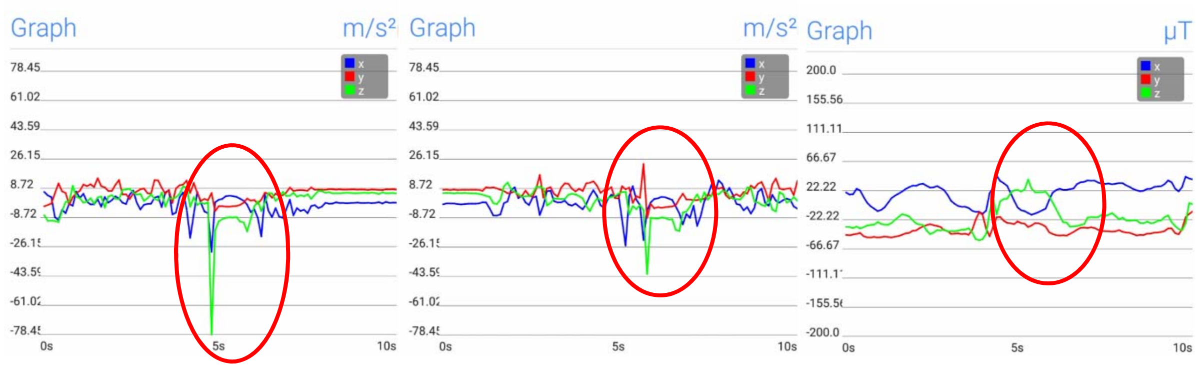

Fig. 4. Values of the accelerometer (first two graphs) and magnetometer (the third graph) when a left dive is performed

The next KPI that we focused on was the jump height. This can be easily computed based on the acceleration from the Y axis. Starting from the known height values for differnet types of jumps and the acceleration needed to leave the ground, we computed the time that should be spent in air for each type of jump. We used the next formula:

$h_{jump} = \frac{1}{8} \cdot a \cdot t^2$, where h_{jump} is the height of the jump, a is the acceleration of gravity and t is the total time spent in air.

Based on this we deducted that $t = \sqrt{\frac{h_{jump} \cdot 8}{9.81}}$ so the computed threshold values are: 570 miliseconds or more spent in air will mean a high jump, a time between 400 and 570 miliseconds a medium jump and any jump with less than 400 seconds spent in air will be a low one. This is not the most precise way of determining the height of a jump, but being limited by the three positioning sensors from the Android phone we considered it good enough.

Even though the KPIs related to speed and distance can be computed based on the positioning sensors with a minor error as shown in [11], we preffered the GPS sensor from the smartphone because of the easiness of the computation. It is true that this system will not work indoor, thing that can be a problem for covered stadiums or different variations of soccer that are played indoor (7-a-side football played on artificial grass or futsal). In this case a LPS (Local Positioning System) should be used instead [7].

In order to validate the computed KPIs, we did two sessions of 15 minutes of training with one goalkeeper (the same one that the threshold values were computed on). Both session were video recorded by an action camera to be able to compare the values calculated by our application with the real values obtained after the video analysis of the trainings. The results of the two training sessions are available in figure 5 and figure 6.

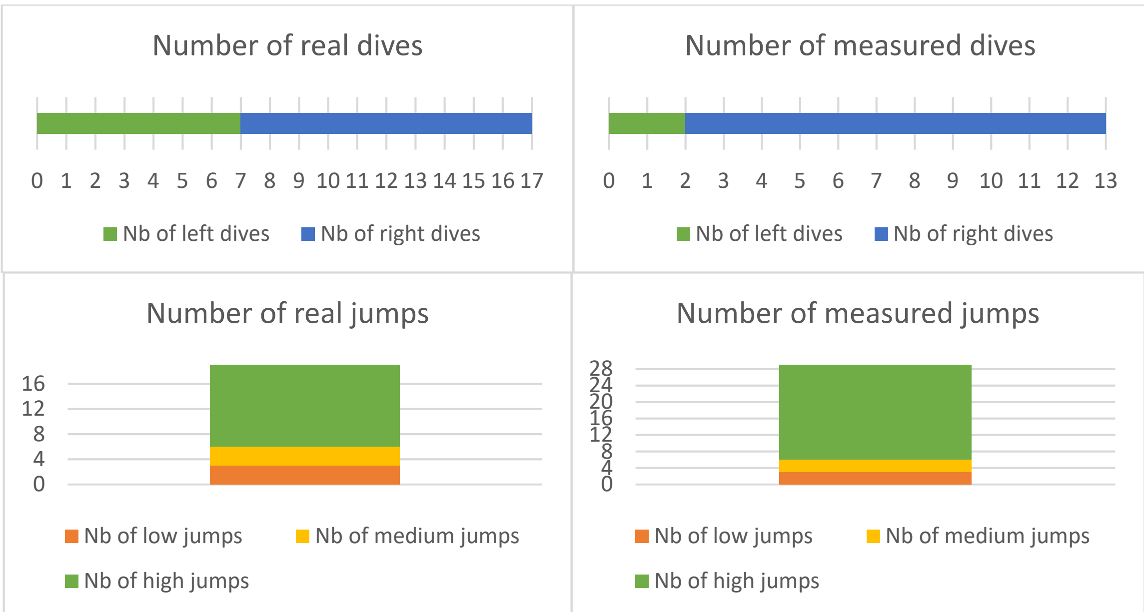

Fig. 5. The results of the first session of training

By comparing the real measurements with the computed ones we observed a slightly tendancy for not counting all the left dives. This can be caused, in our opinion, by the fact that the goalkeeper was not feeling confortable on jumping on the phone's side (left side). We base our opinion on the video analysis of the tranings because we observed there that the right dives were "cleaner" than the left ones, where the goalkeeper seemed inconfortable to jump directly on the phone. Another cause can be the fact that, by placing the phone on the left arm, we had to take a greater threshold for left dives than for right dives, thing that could have affected the final values. We think that this problem can be improved in our next version of the wearable device, by using a small custom device instead of a phone and placing it between the shoulder blades of the goakeeper in a tight vest.

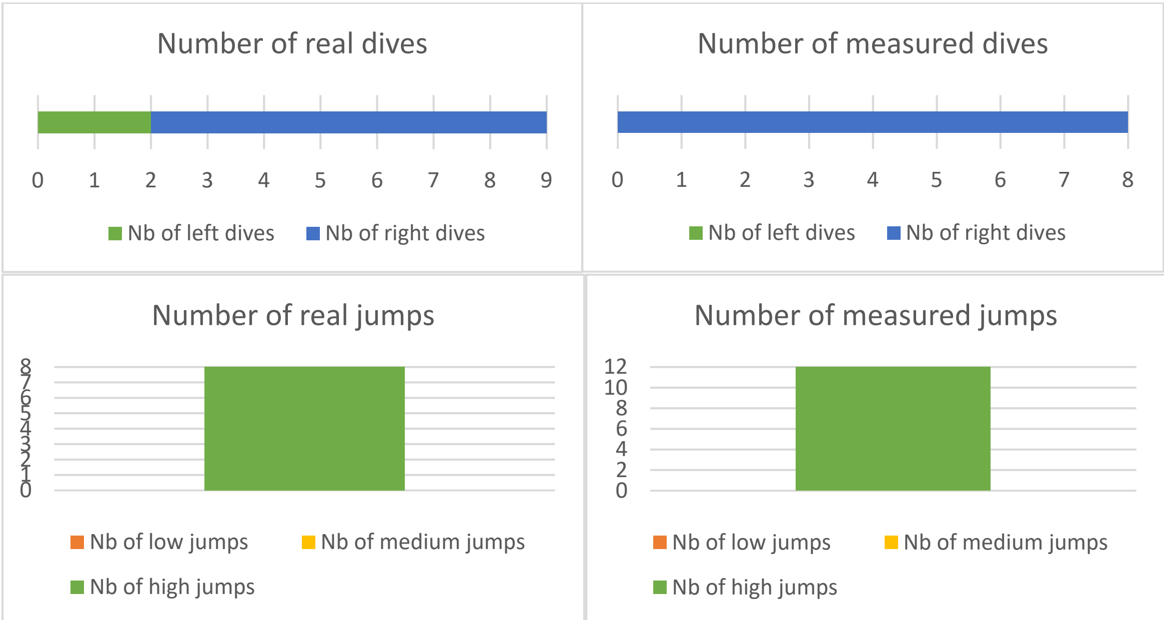

Fig. 6. The results of the second session of training

Regarding the jump height, we observed a tendancy to overestimate the number of high jumps. One possible cause for this, that was observed in the video analysis phase, is the fact that some of the left or right dives that were done in the top corners of the goal were counted as high jumps. We will try to improve this thing also in the next version of our wearable device.

To find out if the results obtained are statistically significant or not we used the standard chi-square test with a significance level of 0.05 [12]. We computed the p value for four degrees of freedom in the case of the first training session and two degrees of freedem in the case of the second one (we excluded the zero measurements for expected values here). The chi-square test results confirmed us that there are significant differences between the real and the expected values in the case of the first training ($p < 0.05$) and not significant differences in the case of the second one ($p > 0.05$). Based on these results we concluded that by fixing the problems with the overestimation of the high jumps and the underestimation of the left dives we can obtain a cheap version of an EPTS wearable device with good precision levels. The final statistics related to the two training sessions are presented in the table below.

Table 1. Chi square test values for the observed data

	Training session	Left dives	Right dives	Low jumps	Medium Jumps	High jumps	p
Real value	#1	2	11	3	3	29	0.000107
Expected value	#1	7	10	3	3	13	
Real value	#2	0	8	0	0	12	0.126006
Expected value	#2	2	7	0	0	8	

4 Conclusions and future work

In this paper we presented the proof-of-concept of a cheap wearable device that can perform goalkeeping analytics in real time. FIFA approved this year the usage of this kind of devices during matches, but beside the high

price of this kind of devices, just a single producer developed a wearable device designed especially for goalkeepers. Based on the KPIs identified by the market leader of this domain we created an Android application for computing the values for these metrics. The device was built using the positioning sensors of an old Android phone and was tested in some real case scenarios. The results obtained were encouraging (with a low significant differences in the case of a training session), even though the application seemed to have a tendency to bias data towards right dives and high jumps.
The next step in our project will be to build a smaller version of the wearable device by using an Arduino board with some positioning sensors attached to it. This second version of our device will be place in a special designed pocket attached to a tight vest worn by the goalkeeper, as most of the EPTS producers do. In this way we can remove the bias caused by the fact that the device is attached right now to the left arm of the goalkeeper.
Future plans include testing the embedded system with multiple goalkeepers in soccer, mini-soccer and futsal matches or trainings.
If the precision obtained by the developed algorithm (the current one which is based on threshold values) will not increase for the next versions of our device, we consider also using supervised machine learning algorithms [13] to compute the KPIs. This has the advantage of obtaining more precise results, but the disadvantage of longer periods of time needed for collecting and labelling data.

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Bogdan IANCU has graduated The Faculty of Cybernetics, Statistics and Economic Informatics from The Bucharest University of Economic Studies in 2010. He has a master’s degree in Economic Informatics (2012) and a PhD degree in Economic Informatics achieved in 2015 in the field of Ontologies and eLearning. He is an Assistant Lecturer in The Department of Economic Informatics from The Bucharest University of Economic Studies. His current research focuses on semantic technologies and ontologies innovations. Other fields of interest include machine learning, cybersecurity, mobile devices and IoT.