Assessing Header Impacts in Soccer with a Smartball

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ABSTRACT

Heading the ball is a fundamental skill in soccer. But, recent studies have shown that players who headed the ball frequently were more vulnerable to concussion. To record head impacts and flag potential concussions, intra-oral and head-mounted devices such as Vector MouthGuard and Biosystems xPatch have been developed. However, they are yet to gain wider acceptance, perhaps because they are inconvenient and expensive. Since headers involve contact with the ball, we leverage this unique opportunity in soccer to explore using a smart ball for monitoring headers. We develop a method to assess the impact of headers using the Adidas micoach soccer ball and compare its performance with that of the xPatch. We find that, while micoach ball is somewhat limited in its sensing capabilities, there is enough promise that a similar ball with a better accelerometer can be an affordable and convenient alternative for monitoring and preventing concussions in millions of soccer players.

1. INTRODUCTION AND MOTIVATION

Soccer is the world's most popular game with over 4 million registered players in the U.S.A. alone, according to FIFA, and countless more unregistered players all over the world. The deliberate use of the head to control the ball is a necessary skill for a successful player regardless of the position: defender, midfielder, or striker. Proper heading technique requires body coordination and proper timing. The player hyperextends the neck, trunk, and hips with the arms out to provide balance. Forward flexion of the trunk generates power, and the neck flexes forward and contracts so that the forehead strikes the ball [12]. Based on measurements at soccer practice with a radar gun, rough estimate of ball speed for punts is 45 MPH, and drop kicks and goal kicks is 55 MPH [12].

Due to the large number of players and the purposeful use of the head during play, traumatic brain injury to soccer players has been a concern for decades. However, there is a sense of urgency now in understanding and preventing concussions better, due to raising public awareness, media coverage [5, 6], and recent movies like *Concussion*. Barnes et al [8] surveyed the 137 soccer players at the US Olympic Sports Festival and found that over one half of men and over one third of women had a history of concussion. They estimated a 50% risk of concussion when playing at this level of competition for 10 years. Boden et al [10] estimated roughly 1 concussion per team per season based on their prospective 2-year data involving Atlantic Coast Conference (ACC) collegiate soccer. According to a recently published study [15], players who headed a lot of balls, an average of 125 over two weeks, were three times more vulnerable to concussion than those who headed less than four in that time period.

Considering the consequences of concussions and the concerns of players and their parents, there has been a significant interest in monitors that measure the force imparted to an athlete's head. When attempting to develop techniques for kinematic measurements during heading, Shewchenko et al [11, 14] chose intra-oral devices to measure linear as well as angular accelerations of the head in a laboratory, based on previous reports of the scalp decreasing impact force by up to 20 times. Recently, University of South Carolina has signed an agreement with i1 Biometrics, so that Gamecocks football team wears Vector MouthGuards [2], to measure the athlete's head's linear and rotational accelerations from impacts experienced in practices and games.

Given the players' natural distaste for such intra-oral devices, it is not surprising that more palatable alternatives for head impact monitoring are being developed. Figure 1 shows some of these devices that are currently available in the market. X2 Biosystems xPatch [7] is an electronic skin patch that is worn behind the ear. Reebok Checklight [3] embeds the impact sensor in the back of a skullcap which can be worn with or without a helmet. Triax SIM-P [4] is placed inside a headband for non-helmeted sports and a skullcap for helmeted sports. While all these devices are much more convenient to wear than intra-oral devices, it is yet to be seen whether they gain wider acceptance, particularly by the millions of amateur soccer players all over the world.

Figure 1: Sensors for monitoring the impact to head: (a) X2 Biosystems xPatch, (b) Reebok Checklight, (c) Triax SIM-P.

Instead of mounting sensors on the players' heads, we wondered, why not embed the sensors and smartness in the ball? Such a smartball is ideally suited for soccer, since headers, which involve contact with the ball, can cause concussions[1]. Therefore,

[1]While head-to-head and head-to-ground impacts also cause

it is conceivable that impact of headers can be measured by the sensors inside the smartball. Imagine a smartball that beeps (perhaps literally during practice and wirelessly to a monitor on the sideline during official games) upon a "dangerous" header, indicating that the corresponding player needs attention.

There are many advantages with such a smart soccer ball. 1) Instead of 22 players in a game wearing head mounted devices (without forgetting), a single smartball can help monitor impacts on all of them. 2) Once the technology is proven to be accurate, it will likely be deployed rapidly in professional leagues, as there will be less resistance to adoption from players. 3) Rapid adoption of the smartball leads to mass production, bringing down its cost significantly. 4) Affordable price brings the technology within the reach of millions of amateur players too, extending safety features to a wider population of soccer players. For all these reasons, it is worth investigating the potential for a smart soccer ball to measure header impacts and mitigate concussions.

This project, as illustrated in Figure 2, aims to employ a smartball to approximate the performance of a sensor like xPatch worn behind player's ear. Towards that end, we explore using the Adidas micoach soccer ball, which is currently available in the market, for monitoring headers. We develop a method to assess the impact of headers using the micoach ball and compare its performance with that of the xPatch. We find that, while micoach ball is somewhat limited in its sensing capabilities, results show great promise that a similar ball with a better accelerometer can be an affordable and convenient alertnative for monitoring and preventing concussions in millions of soccer players.

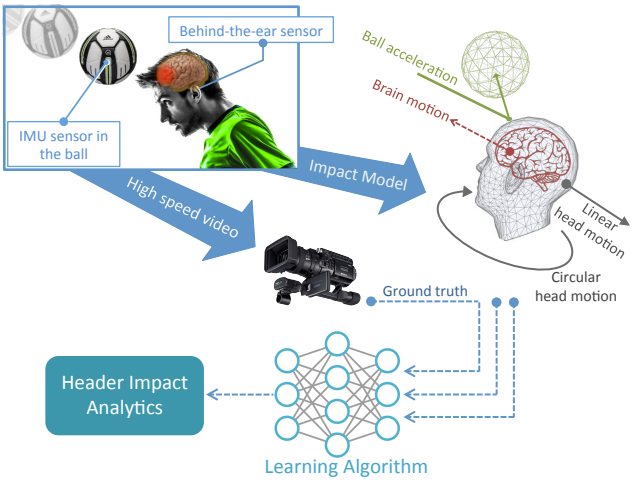

Figure 2: This project aims to learn the correlation between the acceleration of the ball measured by its IMU sensor and the acceleration of the head measured by the xPatch sensor worn behind the ear during a header. If successful, we can flag dangerous headers and record cumulative impacts with a smartball alone without players wearing sensors on their heads.

The rest of the paper is organized as follows. Next, we present the details of the Adidas micoach soccer ball. Then, we describe our experimental setup. In Section 4, we explain the method for estimating the acceleration of the head due to a header using the smartball sensor data and compare its performance with that of the xPatch. We also show that a smartball with a better accelerometer can approximate the performance of xPatch. Section 5 discusses future work and Section 6 concludes the paper.

concussions, cumulative effect of headers can be quite significant [15]. To avoid potential concussions due to headers, the US Soccer Federation has banned headers for players under 11.

2. ADIDAS MICOACH SOCCER BALL

While there is no smart soccer ball that fits our vision perfectly, Adidas recently released the micoach soccer ball [1], shown in Figure 3(a). It is a size 5 regulation weight soccer ball marketed for dead-ball kick training. Upon a kick, the companion app displays the speed, spin, and flight pattern of the ball. But, this information is inadequate for our purpose of studying header impacts. Therefore, we need to develop a new app to estimate the force of a header impact. Unfortunately, the ball's internal hardware and its API are not publicly available. Hence, we have to infer the operation of the smartball first. In the following, we present our findings about the micoach soccer ball.

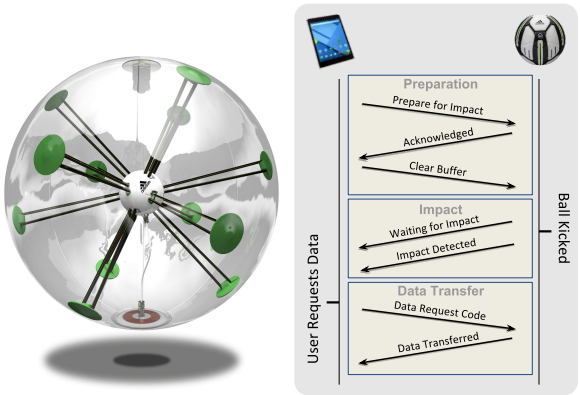

Figure 3: (a) Adidas micoach smartball; (b) The (inferred) protocol between the app and the ball to initiate a kick and gather the corresponding accelerometer readings.

Hardware: The smartball contains LSM3032 chip with tri-axial digital linear acceleration sensor, MSP430F5328 micro controller, and nRF8001 Bluetooth chip. These three components are on a single board which is enclosed in a plastic sphere of about 1.5 inches in diameter. This sphere is suspended in the middle of the ball by 12 bands, which are connected evenly around the surface of the sphere, in the same configuration as the faces on a regular dodecahedron. In addition to these 12 connections, there is a power cable that connects the board to the induction charging coils on the interior of the ball's surface.

Communication Protocol: The smartball communicates with the companion app (say RealApp) via Bluetooth Low Energy (BLE). To decipher the protocol between them (see Figure 4), we develop two Android apps using standard BLE libraries: EmuApp to emulate the companion app and EmuBall to emulate a smart ball itself. To eavesdrop on the communication between smartball and RealApp, when RealApp sends a message, it is recorded by EmuBall which passes it to EmuApp, which relays it to the smartball. Similarly, the response from the smartball is received by EmuApp and relayed to RealApp via EmuBall. The inferred protocol between RealApp and smartball to initiate a kick and gather accelerometer readings is shown in Figure 3(b).

Recording Headers: Given the current operation sequence of

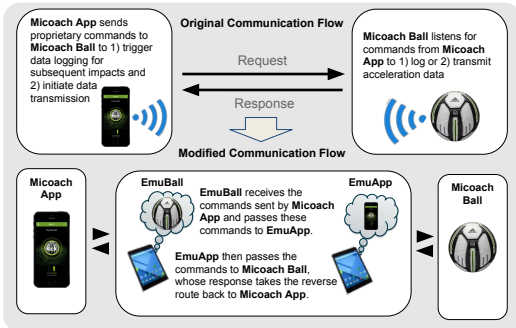

Figure 4: Process used for inferring the unknown communication protocol between the smartball and its companion app.

the smartball, that records kicks when the ball is stationary, an improvisation is needed to measure the impacts of headers. The revised sequence of operations is as follows. Once the app issues a prepare-to-kick command, the ball notifies the app the moment it has been kicked. Next, instead of requesting the accelerometer readings, the app issues another prepare-to-kick command, when the ball is midair. Then, the ball treats the header (or any other contact) as equivalent to kick and notifies the app. Now, the app requests for the accelerometer readings and derives the force of the header impact.

Accelerometer Readings: We find that the acceleration samples given by the ball are represented as signed (2's complement) 16 bit integers, with maximum and minimum values of 2040, and -2039, respectively. To map them to the real acceleration values, we need to know the maximum measurable acceleration range. The smartball's accelerometer chip, LSM3032, offers 4 options for selecting the maximum acceleration range (and sensitivity per least significant bit): $\pm 2g(1mg), \pm 4g(2mg), \pm 8g(4mg)$, and $\pm 16g(12mg)$. To infer the smartball's accelerometer range setting, we consider the stationary acceleration, which is found to be around 511. By mapping 511 to $1g$, we can infer that acceleration range and sensitivity of the smartball to be $\pm 4g$ and $2mg$/LSB. We also observe that after each impact, we receive 1000 samples of accelerometer data per second.

Problem of Saturation due to Accelerometer Range: A key challenge in estimating the header impacts from the accelerometer data from the smartball is that the range is only $\pm 4g$, while the acceleration for even a small impact is much higher. To illustrate this, in Figure 5, we contrast the acceleration measured by the smartball and that by an external sensor, with a range of $\pm 200g$, stuck on the surface of the ball, when the ball is dropped from a height of less than one feet. Even for such a small impact, the truncation of the peaks, particularly those immediately after the impact, is evident from the accelerometer data of the smartball.

Preliminary Validation: Even with truncated accelerometer values, fortunately, the acceleration experienced by the ball's sensor has a relationship with the impact force. To gauge the ball sensor's potential for discriminating different forces, we developed a machine learning based method to estimate the impact force by training it with handpicked features. These features include the width of the first peak which is proportional to the impact time, the amplitude of the subsequent peaks which is a function of the damping factor and the magnitude of the acceleration until the total energy drops below the 10% of the first peak. We conduct

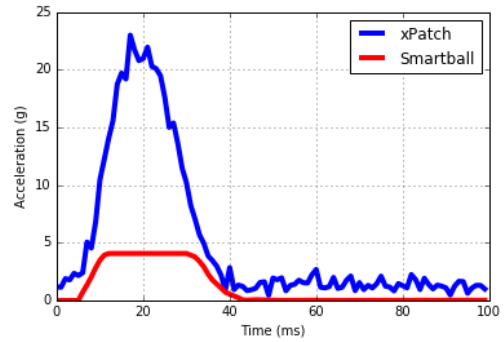

Figure 5: Acceleration data from the smartball (range of $\pm 4g$) and from the external sensor (range of $\pm 200g$)

a preliminary validation of our approach using a piezo-electric sensor based force estimation setup, called *force-pad*, commonly used for precision force measurement. Force-pad uses three force sensors to record the varying force at 500 KHz and log it in an oscilloscope in realtime. We simultaneously collect the acceleration data from the smartball and the impact force from the forcepad as the ground-truth. We trained the model with 175 samples and then tested with another 175 samples. Figure 6 compares the estimated force with the ground-truth when the ball was dropped on the force-pad from different heights. All the points are somewhat closer to the diagonal, affirming the validity of accelerometer readings we gathered from the ball and their potential to discriminate between different impact forces.

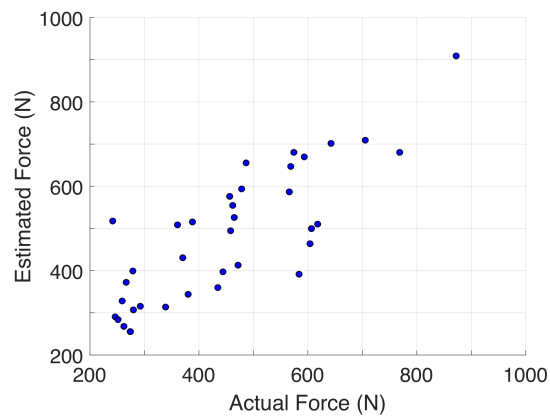

Figure 6: Actual vs estimated force when the soccer ball is dropped on the *force-pad* from various heights.

3. EXPERIMENTAL SETUP

We now describe the experimental setup used to understand the correlation between the acceleration of the ball measured by its IMU sensor and the acceleration of the head measured by the xPatch sensor. To model the dynamics of a ball's impact on a player's head, we employ a mannequin to 'head' a smartball that is propelled at it. The experimental setup for the mannequin consists of a Century BOB (Body Opponent Bag) dummy fitted with two xPatches, one behind each ear. Meant for being subjected to a variety of blows, this dummy is durable enough to withstand and undergo significant header impacts. Initial tests found that foam placed inside the dummy, to prevent injury to an assailant's fists, caused it to deform unrealistically on impacts

from the ball. The foam inside the head was removed and replaced with a hard plastic shell filled with ballast to better mimic the hardness and mass of a real player's head. Additionally, a wooden pole was inserted down the back of the dummy to prevent the head from bending unrealistically backwards, providing a rough approximation of a player's neck and spinal column. To propel the ball, we use a JUGS Soccer Machine, which can propel the ball at regulated speeds of up to 100 mph and allows for easy collection of header data. The launching speed of the machine was verified to within ± 2 mph using a Bushnell Velocity Speed Radar Gun. Figure 7 illustrates our experimental setup.

Figure 7: Our setup with soccer machine, ball, and dummy.

Each xPatch behind the ear records 100 samples of linear and rotational acceleration for each impact event and it can store information for over 1600 impact events. The sampling rate of the xPatch is 1 KHz and its linear accelerometer has a range of $\pm 200g$ (for the experiments reported in this paper, we only consider linear acceleration). Before examining the relationship between the smartball and xPatch measurements, the existence of the more fundamental linear relationship between the smartball motion around the impact and xPatch measurement is validated through analysis of slow motion video capture of several impacts, gathered at machine speed settings of 20 through 40 mph (approximately 9 through 18 m/s). The speed of the smartball prior to and immediately following each impact, as well as the duration of the impact, measured as the time the ball is in contact with the head, is determined from a frame by frame analysis of each video, taken at 960 FPS. Based on these values, the deceleration of the smartball is computed and compared to the acceleration measured by the xPatch. Figure 8 illustrates the relationship between them and confirms that they are very well correlated.

4. HEADER IMPACT ESTIMATION

As mentioned earlier, the smartball's accelerometer has a range of only $\pm 4g$. A comparison with an external sensor (range $\pm 200g$) shows how this limitation creates plateaus in the smartball data due to sensor saturation (Figure 5). Using a method similar to [9], we attempt to reconstruct missing peaks in the data but found that the truncations were too severe for accurate reconstruction, as a typical impact can easily exceed 100g – well above the 4g limit. Instead, we leverage ensuing reverberations of the ball's internal sensor after an impact and develop a method based on machine learning. Specifically we use Bayesian Ridge Regression, which, similar to classical Ridge Regression, utilizes l2-norm regularization to address possible overfitting. Unlike Ridge Regression, the regularization parameter is estimated in the Bayesian formulation as part of the training process. Additionally, an IsolationForest [13] is used to detect anomalies in the data set and remove these outliers prior to training the model.

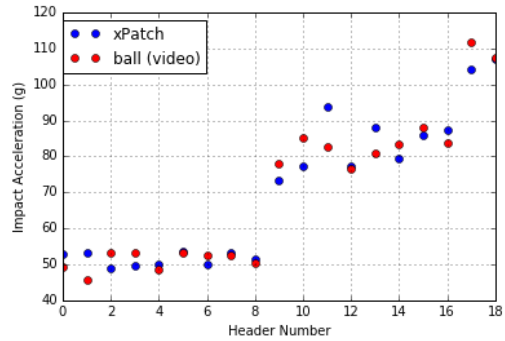

Figure 8: Correlation between deceleration of the ball computed from the slow motion video and acceleration of the head measured by the xPatch (scaled to demonstrate correlation).

Using the experimental setup shown in Figure 7, we collect 100 impacts each for speeds of 20, 30, and 40 mph. Only impacts where the smartball collides solidly with the dummy's head were recorded for these experiments. Taking the average impact acceleration experienced by the xPatches on the dummy as ground-truth, we train our model using the features extracted from the smartball's internal sensor data (using a 75%/25% train/test split of the data). This average acceleration is computed over a 100 ms interval encompassing the impact. We observe that the data from both xPatches on the dummy varies only slightly between position on either side of the head, so we average their readings together for these experiments. Figure 9 shows that our method, while not quite accurate, performs within ±11% xPatch.

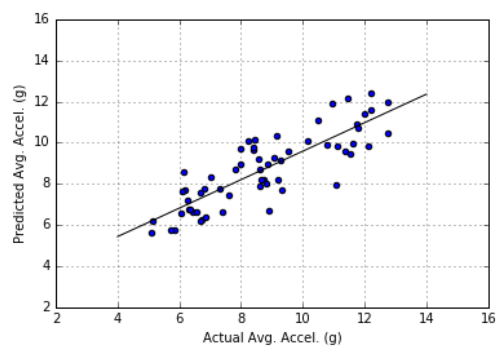

Figure 9: Average impact acceleration of xPatch versus predicted output of model using smartball's $\pm 4g$ internal sensor.

We hypothesize that the inaccuracies seen in the previous results stem from the limitations of the micoach ball's internal sensor whose acceleration range is only $\pm 4g$. To test this hypothesis, we stuck an accelerometer sensor with a range of $\pm 200g$ externally on the ball (referred to as external sensor), and repeated experiments using this sensor as our source of data for the training the machine learning model. Figure 10 illustrates that the performance of the model has improved with the new sensor to within ±5% xPatch. This is quite an encouraging result, as we can expect that the next generation of balls similar to micoach ball will likely embed a better accelerometer and thus help the smartball approximate the performance of xPatch.

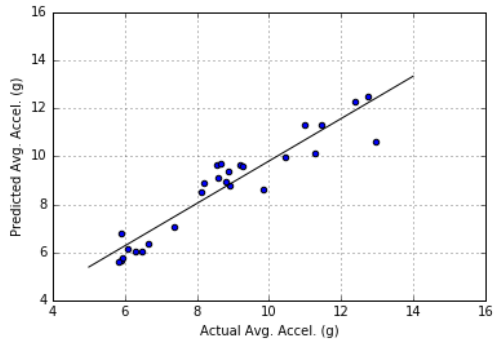

Figure 10: Average impact acceleration of xPatch versus predicted output using external $\pm 200g$ sensor placed on smartball.

During the game, apart from determining the acceleration of the head due to a header, it helps to flag a particularly hard header. Then, the corresponding player may be taken off the field and examined to ensure the safety of the player. Towards that end, we developed a classifier that separates hard headers (> 10g) from the rest. We chose a Gaussian naive Bayes classifier for our model due to the relatively small size of our training data set. Figure 11 shows the performance of this binary classifier for both smartball's internal and external sensors. As expected, external sensor with a larger accelerometer range can accurately determine hard headers. Even with limited range internal sensor, smartball also performs reasonably well in identifying hard headers.

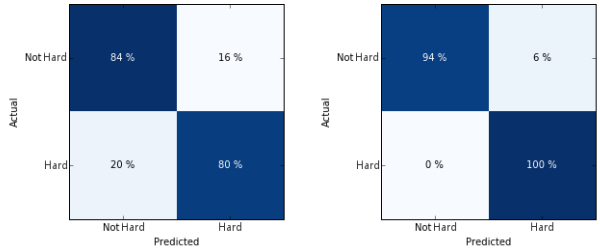

Figure 11: Classification of headers as hard or not hard using the ball's (a) internal ($\pm 4g$) (b) external ($\pm 200g$) sensor.

5. ON-GOING AND FUTURE WORK

Our experimental results show that the proposed approach of using smartball to assess header impacts has great promise, particularly if the smartball could be embedded with a better sensor. However, to substantiate our conclusions, we are currently collecting more and varied impacts to bolster our dataset. Additional data will provide further insight and will allow for more flexibility in selecting and training more sophisticated models. This will also help us investigate what is the best possible performance with currently available smartball sensors and whether and how well better sensors would approximate wearable sensors like xPatch. Rather than focusing on analyzing individual impacts, we plan to look at sequences of events, as aggregated information may more accurately encompass the cumulative effects of multiple impacts on a player's head.

Another immediate future work is to determine how the measured acceleration values corresponding to an impact relate to damage to a player's head. We will investigate how the quantities measured for the dummy translate to a real player. We are currently seeking IRB approval to begin collecting impact data for soccer players from local adult club soccer leagues. Moving beyond simply measuring header impacts to determining their consequences on the brain is our long term objective.

6. CONCLUSION

The increased awareness of the harmful effects on the brain incurred from heading the ball in soccer make impact monitoring devices essential. Existing intra-oral and head-mounted sensors inconvenience players and may not be affordable for millions of amateur players. By illustrating the promise in using a smart soccer ball to measure the quantities from a head/ball impact, we have taken a step towards eliminating the need for such devices and helping make impact monitoring available to all.

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