On Smart Soccer Ball as a Head Impact Sensor

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***Abstract*— Heading the ball is a fundamental skill in soccer. However, recent studies have shown that players who headed the ball frequently were more vulnerable to concussion. To record head impacts and flag potential concussions, intraoral and head-mounted devices such as Vector MouthGuard and Biosystems xPatch have been developed. However, they are yet to gain wider acceptance among soccer players, 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 smartball 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 the micoach ball is somewhat limited in its sensing capabilities, there is enough promise that a similar ball with a more precise accelerometer can be an affordable and convenient alternative for monitoring header impacts in soccer.**

***Index Terms*— Accelerometer, concussion, injuries, sensor systems and applications, sport equipment.**

I. Introduction

SOCCER is the world's most popular game with over 4 million registered players in USA alone, according to Fédération Internationale de Football Association, 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. The 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 [17]. Based on measurements at soccer practice with a radar gun, a rough estimate of ball speed for punts is 45 mph, and drop kicks and goal kicks are 55 mph [17].

Due to a 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.* [10] surveyed the 137 soccer players at the U.S. 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.* [13] estimated roughly one concussion per team per season based on their prospective 2-year data involving Atlantic Coast Conference collegiate soccer. According to a recently published study [21], 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 times during the same 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, Gurdjian *et al.* [16] and Shewchenko *et al.* [20] chose intraoral 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 [1], 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 intraoral devices, it is not surprising that more palatable alternatives for head impact monitoring are being developed. Fig. 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 [2] embeds the impact sensor in the back of a skullcap, which can be worn with or without a helmet. Triax SIM-P [3] is placed inside a headband for nonhelmeted sports such as soccer and a skullcap for helmeted sports like football. Although all these devices are much more convenient to wear than intraoral devices, it is yet to be seen whether they gain wider acceptance, particularly by the millions of amateur soccer players all over the world.

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, it is conceivable that impact of headers can be

Manuscript received March 6, 2018; revised July 25, 2018; accepted August 28, 2018. Date of publication October 12, 2018; date of current version July 12, 2019. The Associate Editor coordinating the review process was V. R. Singh. *(Corresponding author: Srihari Nelakuditi.)*

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Digital Object Identifier 10.1109/TIM.2018.2872307

[1] While head-to-head and head-to-ground impacts also cause concussions, the cumulative effect of headers can be quite significant [21]. To avoid potential concussions due to headers, the U.S. Soccer Federation has banned headers for players under 11.

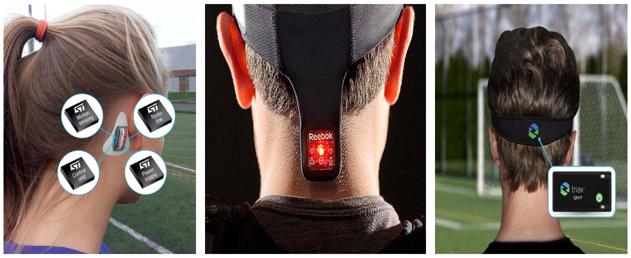

Fig. 1. Sensors for monitoring the impact to head. (a) X2 Biosystems xPatch. (b) Reebok Checklight. (c) Triax SIM-P.

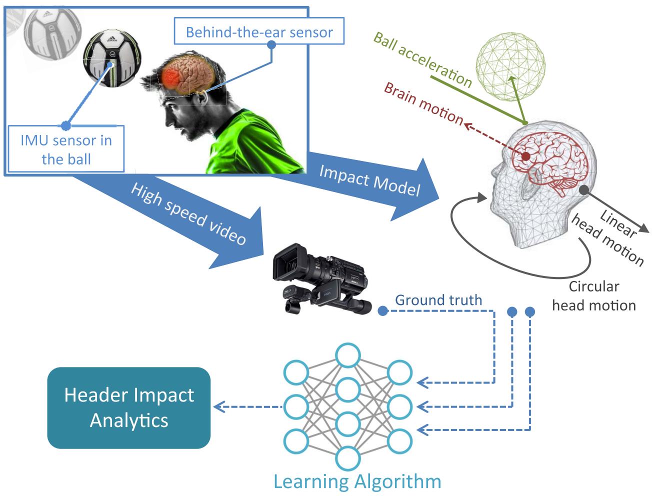

Fig. 2. This project aims to learn the correlation between the acceleration of the ball measured by its IMU sensor and the acceleration of the head measured by the xPatch sensor worn behind the ear during a header. If successful, we can flag dangerous headers and record cumulative impacts with a smartball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

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 is likely to lead to mass production, bringing down its cost significantly; and 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 all over the world. 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 Fig. 2, aims to employ a smartball to approximate the performance of a sensor such as xPatch worn behind player's ear. Toward 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

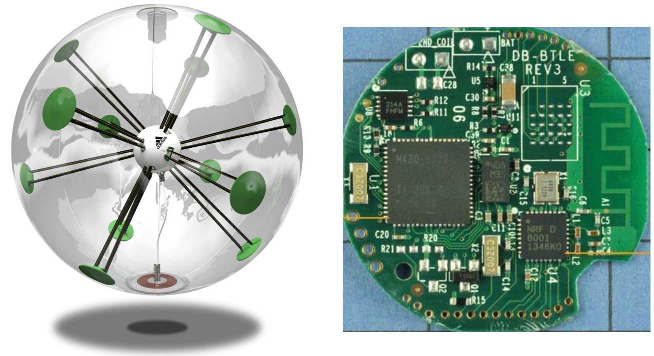

Fig. 3. (a) Adidas micoach smartball. (b) Sensor board with the accelerometer positioned at the center of the inner sphere.

that, while the 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 alternative for monitoring and preventing concussions in millions of soccer players.

The rest of this paper is organized as follows. Next, we describe the Adidas micoach soccer ball. Then, we present our experimental setup. In Section IV, 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 VI discusses the ongoing and future work and Section VII concludes this paper.

II. Adidas Micoach Soccer Ball

While there is no smart soccer ball that fits our vision perfectly, Adidas released the micoach soccer ball [9] in May 2014, shown in Fig. 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. 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 air position indicator 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.

A. Hardware

The micoach ball contains STMicroelectronics LSM303DLHC chip with a triaxial digital linear acceleration sensor, Texas Instruments MSP430F5328 microcontroller, and Nordic Semiconductor nRF8001 Bluetooth chip. All chips are powered by an internal lithium battery, charged with an induction system that does not require compromising the surface of the ball. The battery charge is sufficient for several hours of constant use or for a week of inactivity. All acceleration values returned by the LSM303DLHC are represented as signed integers of 12-bits left-aligned in a 16-bit space. Note that while this chip also contains a triaxial

Service		Characteristic			
UUID	Name	UUID	Mnemonic	Default Value	Access
1800	Generic Access	2A00	Device Name	DB00XXXXX	R/W[1]
		2A01	Appearance	911	R
		2A04	Peripheral Preferred Connection Parameters	13107206[2]	R
1801	Generic Attribute	2A05	Service Changed	0	I/R
180A	Device Information	2A23	System ID	various	R
		2A24	Model Number String	nrfXXXXX	R
		2A25	Serial Number	various	R
		2A26	Firmware Revision String	3.5 (currently)	R/W
		2A28	Software Revision String	Rev1.0	R
		2A29	Manufacturer Name String	Adidas AIT	R
180F	Battery Service	2A19	Battery Level	varies	R
AD04 Smart Ball Service		AD13	???	0	N/R
		AD14	Logging Characteristic	0	N/R
		AD15	Command Characteristic	N/A	WNR
		AD16	Firmware Write Field	N/A	W
		AD17	Response Buffer Characteristic	N/A	N
		AD20	Sample Rate Characteristic	[1,0]	N/R
		AD1F	Status Characteristic	varies	R
		ADFE	Error Characteristic	varies	N/R
		AD12	Kick Event Characteristic	varies	N/R
		AD33	File Size Characteristic	varies	R
		DB55	???	N/A	N

[1] Even though this characteristic has write access and can be edited, it is reset to its default value automatically every time the ball is charged.
[1] This value signifies: min connection interval = 6, max connection interval = 200, slave latency = 0,

Fig. 4. GATT services and characteristics broadcasted by the ball.

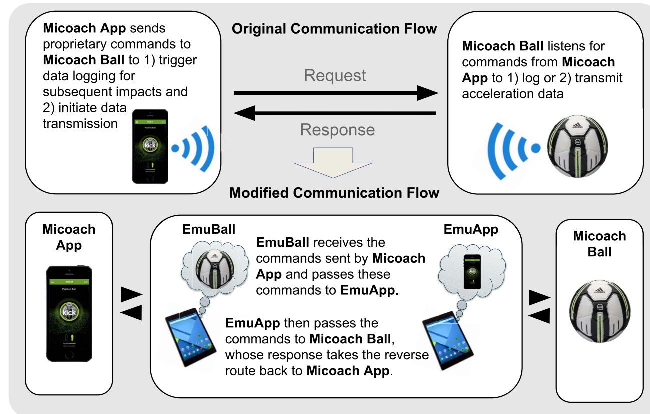

Fig. 5. Process used for inferring the unknown communication protocol between the micoach soccer ball and its companion app.

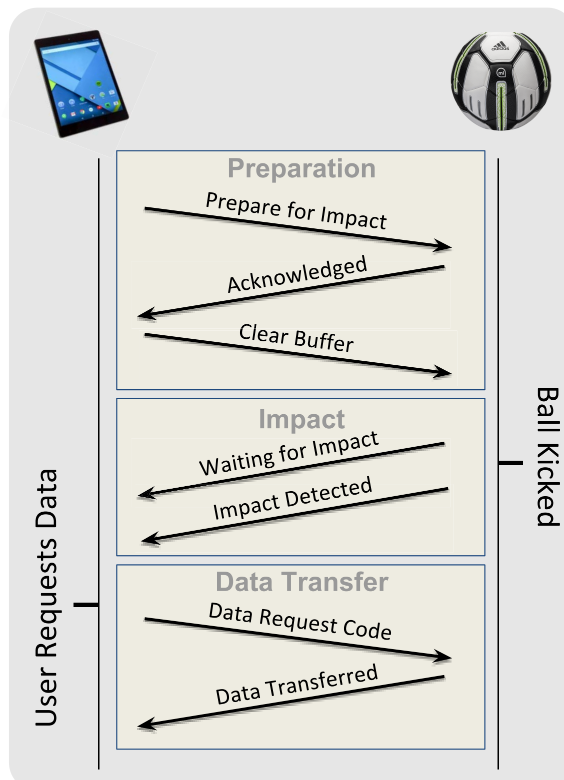

Fig. 6. Protocol (inferred) between the app and the ball to initiate a kick and gather the corresponding accelerometer readings.

gyroscope, to the best of our knowledge, this component is not used by the micoach ball. MSP430F5328 is based on a 16-bit CPU and is designed for low cost and low-power consumption. It does not have an external memory bus and, hence, it is limited to on-chip memory. The nRF8001 is a fully qualified Bluetooth smart v4.0 connectivity IC with integrated radio, link layer, and host stack supporting peripheral (slave) role operation.

These three components, accelerometer, microcontroller, and Bluetooth, are on a single board which is enclosed in a plastic sphere of about 1.5 in 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 bands, there is a power cable that connects the board to the induction charging coils on the interior of the ball's surface [Fig. 3(a)].

B. Communication Protocol

The smartball communicates with the companion app via Bluetooth low energy (BLE). The smartball broadcasts standard BLE services as well as custom services specific to its functionality. Fig. 4 shows a comprehensive list of generic attribute profile (GATT) services and characteristics broadcasted by the smartball.

To decipher the protocol between the companion app (which is referred to as the RealApp) and smartball (see Fig. 5), we develop two Android apps using standard BLE libraries: EmuApp to emulate the companion app and EmuBall to emulate a smartball 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 Fig. 6. It has three phases. Prior to a kick, the ball is prepared for an impact by clearing the buffer. Upon detecting an impact, the ball notifies the app, which then requests and receives the data corresponding to the impact.

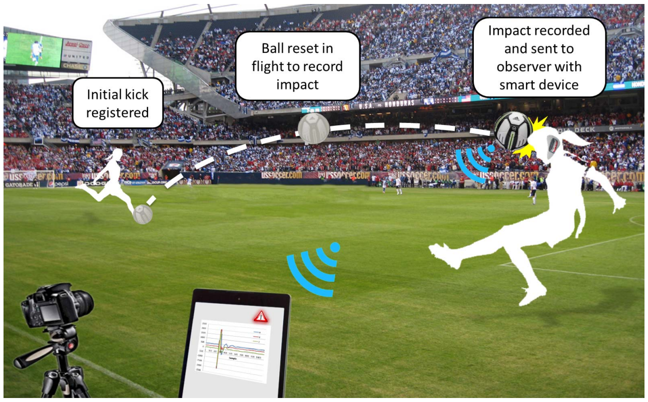

Fig. 7. Operation sequence to record header impact instead of the kick.

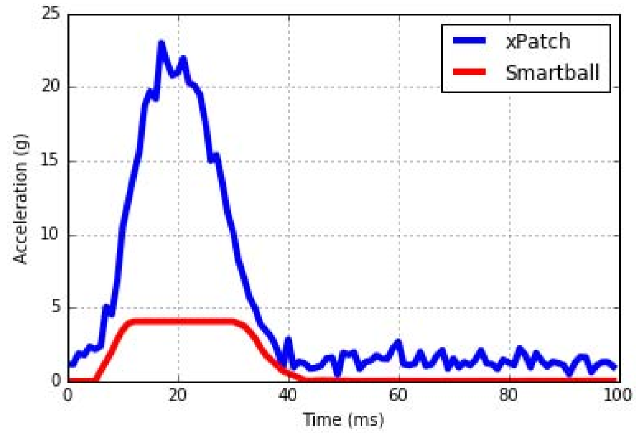

Fig. 8. Acceleration data from a smartball (± 4 g range) and from an external sensor (± 200 g range) when dropped from less than a foot height.

C. Recording Headers

Given the current operation sequence of 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 (see Fig. 7). 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 subsequent impact as equivalent to a kick and notifies the app. If this impact was a header, the app requests for the accelerometer readings and derives the force of the header impact.

D. Accelerometer Readings

We find that the acceleration samples given by the ball are represented as signed (2's complement) 16-bit integers, with the maximum and minimum values of 2040, and -2039, respectively, corresponding to ± 4 g with a sensitivity of 2 mg/LSB. Due to the proprietary nature of the protocol, it is necessary to verify these values through comparison with a device of known specifications. Namely, the smartball's accelerometer chip, LSM3032, offers four possible options for the maximum acceleration range (and sensitivity per least significant bit): ± 2 g(1 mg), ± 4 g(2 mg), ± 8 g(4 mg), and ± 16 g(12 mg). We determine the use of the second setting by noting the difference between the measurements from known and unknown devices, as well as by observing that the stationary acceleration measured by the device (approximately 500) corresponds to 1 g only when using the 2 mg/LSB setting. We verify the device sampling rate to be 1000 Hz by measuring the distance in samples between peaks generated by impact events of known periodicity.

E. Problem of Saturation Due to Accelerometer Range

A key challenge in estimating the head impacts from the accelerometer data from the smartball is that the range is only ± 4 g, while the acceleration for even a small impact is much higher. In Fig. 8, we contrast the acceleration measured by the smartball and that by an external sensor, with a range of ± 200 g, attached to the surface of the ball, when it is dropped from a height of less than one foot. 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.

F. Preliminary Validation

Even with truncated accelerometer values, fortunately, the acceleration recorded 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 extracted from the rms acceleration values over a 100-ms interval containing the impact region and subsequent oscillations. These 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 a preliminary validation of our approach using a piezoelectric sensor-based force estimation setup (Fig. 9), called force-pad, commonly used for precision force measurement. Force-pad uses three sensors to record the varying force at 500 KHz and log it in an oscilloscope in real time.

We simultaneously collect the acceleration data corresponding to each impact from the smartball and the impact force from the force-pad as the ground-truth. We trained the model with 175 samples and then tested with another 175 samples. Fig. 10 shows the comparison of 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.

III. Experimental Setup

We now describe the experimental setup used to understand the correlation between the acceleration of the micoach soccer ball measured by its inertial measurement unit (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

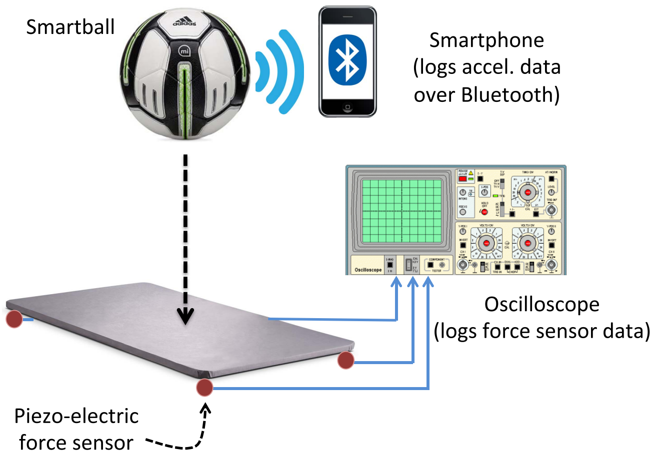

Fig. 9. Force-pad setup to simultaneously record the acceleration data corresponding to the impact from the smartball and the actual force.

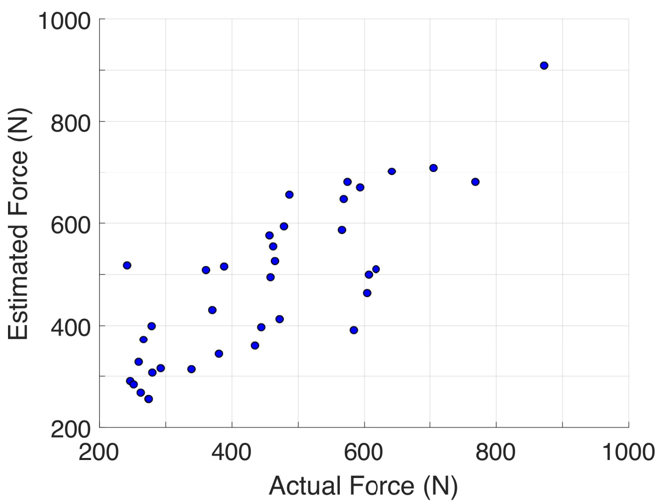

Fig. 10. Actual versus estimated force of each impact when the soccer ball is dropped on the force-pad from various heights.

head, we employ a mannequin to "head" a smartball that is propeled at it. The experimental setup for the mannequin consists of a century body opponent bag (BOB) 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 the mass of a real player's head. In addition, 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. Fig. 11 illustrates our experimental setup.

Fig. 11. Our setup with soccer machine, ball, and dummy.

Each xPatch behind the ear records 100 samples of linear and rotational accelerations for each impact event and 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 ±200 g (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 the 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. Fig. 12 illustrates the relationship between the smartball's deceleration and the acceleration sensed by the xPatch, and confirms that they are very well correlated, with a Pearson coefficient of 0.97, denoting a large effect size according to Cohen's definition [15].

IV. Header Impact Estimation

In this section, we present the methods for approximating head-mounted sensors in estimating the impact of headers from the accelerometer data recorded by the smartball.

A. Acceleration Prediction

As mentioned earlier, the smartball's accelerometer has a range of only ±4 g. A comparison with an external accelerometer (with a range of ±200 g) shows how this limitation creates plateaus in the smartball's accelerometer data due to sensor saturation (Fig. 8). Using a method similar to [12], we have attempted to reconstruct missing peaks in the accelerometer data but found that the truncations were too severe for accurate reconstruction, as a typical impact can easily exceed 100 g—well above the 4-g limit. Fortunately, the accelerometer data shows prolonged oscillation, typically within the 4-g range, for a significant time period (50–100 ms) after the initial impact. Fig. 13 shows the reverberation in one of the axes

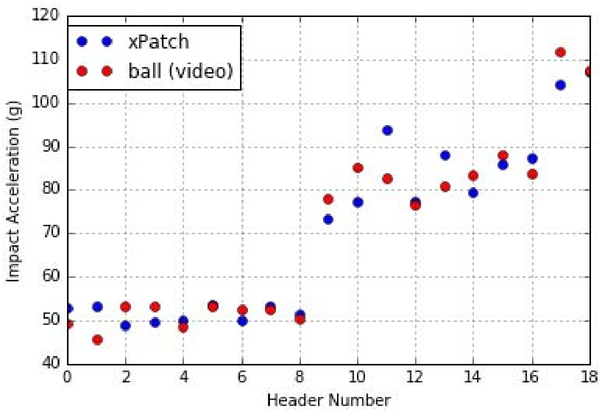

Fig. 12. Correlation between deceleration of the ball computed from the slow motion video and acceleration of the head measured by the xPatch (scaled up uniformly to make the correlation quite apparent).

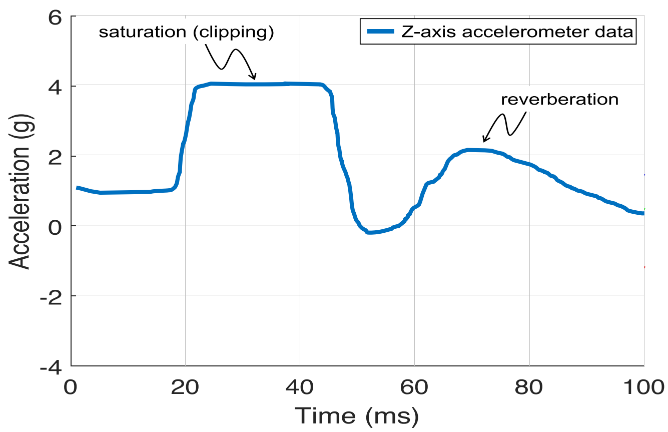

Fig. 13. Illustration of the initial truncation and the ensuring reverberation in a typical accelerometer data corresponding to an impact.

of the accelerometer data. Sensor data during this damped reverberation period is a function of the initial impact as well as the structure of the ball including the sensor mount. Given the rest of the factors remain constant, we leverage this ensuing reverberations to predict the impact acceleration with a machine learning-based method.

Specifically, we employ Bayesian ridge regression, which, similar to the 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. In addition, an IsolationForest [18] is used to detect anomalies in the accelerometer data set and remove these outliers prior to training the model.

Using the experimental setup shown in Fig. 11, 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 statistical features extracted from the smartball's internal accelerometer data, over a 100-ms interval encompassing the impact. In particular, we use the mean (μ_1) and the next three higher moments, $\mu_i = (1/N)\sum_{n=1}^{N}(x_n - \mu_1)^i, i = 2, 3, 4,$

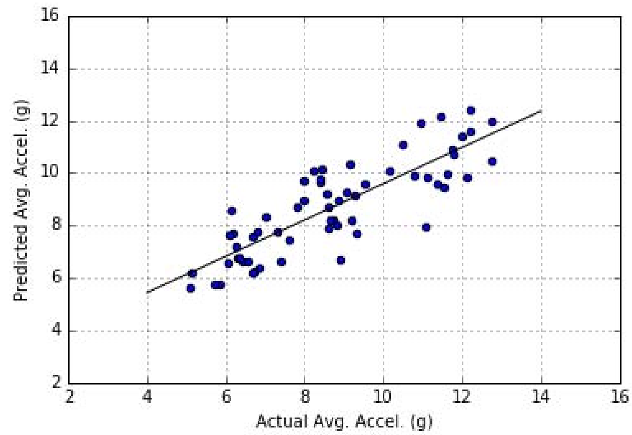

Fig. 14. Average impact acceleration recorded by xPatch versus predicted output of model using smartball's ±4 g internal accelerometer.

as features. These higher moments are known as the variance, skewness, and kurtosis of the data, and are commonly used features in vibration data analysis [14]. In addition, we include the minimum and maximum values of the data as features to capture the range of the recorded acceleration. We extracted these features in both the time and frequency domains. We observe that the data from both xPatches on the dummy vary only slightly between their positions on either side of the head; therefore, we average their readings together for these experiments. Fig. 14 shows that our method for predicting average impact acceleration due to a header performs within ±2.7 g of the xPatch behind the ear, with a Pearson coefficient of 0.83.

B. Impact Alarm Classifier

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 player's safety. To that end, we developed a classifier that separates hard headers, according to a predefined impact threshold.

Choosing the Threshold: Among several factors, the acceleration experienced by the head is probably the most significant factor that leads to a concussion. Human brain, cushioned by the cerebrospinal fluid, is equipped to withstand everyday low acceleration impacts. For example, in a roller coaster, a person experiences around 4.5 g of acceleration without any injury [4]. The acceleration in high impact events, like in a car crash that leads to permanent brain damage, can be 30 g [11]. Although the particular type and the acceleration of the impact that causes concussion are yet to be established, we have considered a moderate value, 10 g, for the hard header threshold in our experiments.

We chose a Gaussian naive Bayes classifier for our model due to the relatively small size of our training data set. Fig. 15 shows the performance of this binary classifier for both smartball's internal and external sensors. Even with limited range internal sensor, smartball performs reasonably well in identifying hard headers. Next, we discuss the potential for improvement over these results.

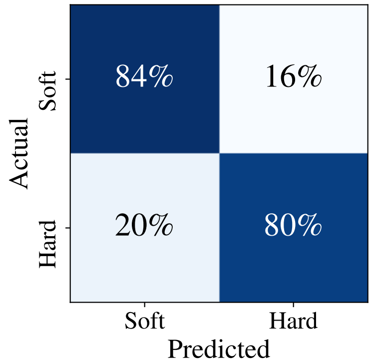

Fig. 15. Classification of headers as hard or not hard using the data from the micoach soccer ball's internal accelerometer sensor.

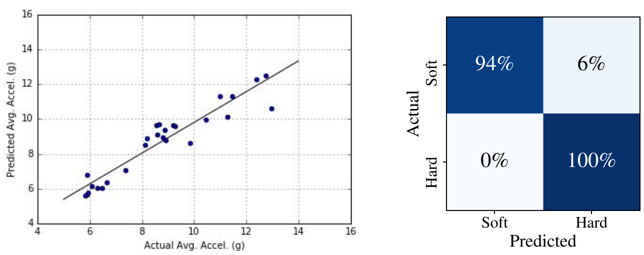

Fig. 16. Experiment with the micoach soccer ball's external ($\pm$200 g) sensor. (a) Average impact acceleration of xPatch versus predicted output. (b) Classification of headers as hard or not hard.

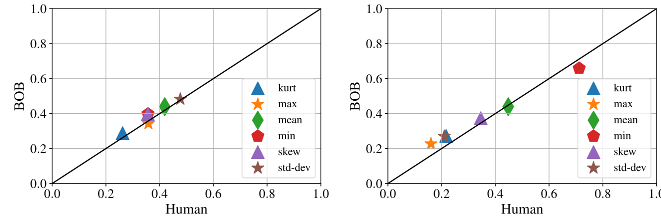

Fig. 17. (a) Features extracted from the ball with dummy and real headers are highly correlated. (b) Same with head-mounted sensors too. In the latter case, this correlation, while still linear, is slightly off the diagonal, indicating that some differences do exist between the head-mounted sensors for human and BOB, but in a predictable way.

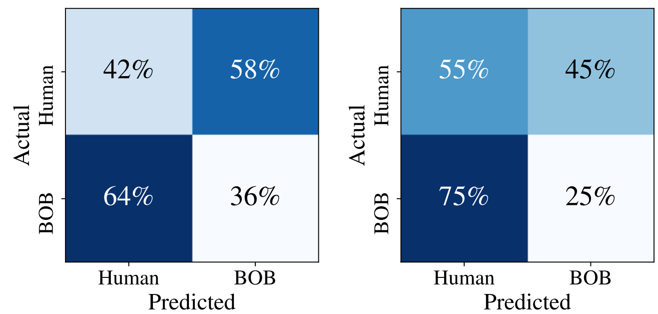

Fig. 18. Classifier fails to distinguish between the dummy and real headers using the (a) ball and (b) head-mounted sensors. The second case is perhaps slightly better, due to the relationship shown in Fig. 17(b).

C. Improving Prediction Accuracy

Although the above-mentioned regression and classification results indicate the promise of the proposed approach in general, further improvement in false positives/negatives is needed for deployment. 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$4 g. To test this hypothesis, we stuck an accelerometer sensor with a range of $\pm$200 g externally on the ball (referred to as external sensor), and repeated experiments using this sensor as our source of data for training the machine learning model. Fig. 16(a) illustrates that the performance of the model has improved with this sensor to within $\pm$1.5 g of the xPatch, with a Pearson coefficient of 0.93. As shown in Fig. 16(b), an external sensor with a larger accelerometer range can accurately determine hard headers with the impact classifier as well. This is an encouraging result, as we can expect that the next generation of balls similar to micoach ball will likely embed a more precise accelerometer, and thus help the smartball better approximate the performance of xPatch.

V. Limitations and Discussion

This paper aims to flag potentially injurious headers, enabling timely attention to the players by the personnel along the sidelines during a soccer game. However, it takes only a small step toward that end, and has several limitations that need to be addressed to make it amenable for deployment. In the following, we discuss some of these limitations, mitigating factors, and possible remedies.

A. Experiments Are Based on a Dummy, Not With Real Players

As described in Section III, we use a BOB dummy instead of real players to simplify the data gathering process. Due to the dynamic nature of a real header, where the player maneuvers his/her upper body to meet and direct the ball, the use of a static dummy may seem inadequate to capture the nuances at play in these events for application to a real scenario. Although, in our work, we simply assess the core potential of these methods, this is an important point to address. To this end, we compare header impacts captured with the BOB dummy at the 20-mph range to 22 headers by two authors at the same speed setting. We do not exceed this speed range to avoid the risk of injury. A statistical analysis of features derived from these impacts (Fig. 17) is unable to determine that a difference exists between these real and dummy headers. Similarly, a Gaussian Naive Bayes classifier model trained on the same features is unable to differentiate the classes (Fig. 18). Although both of these methods may yield more definitive results with a more expansive analysis, we can affirm that at the very least no obvious difference exists between real and dummy headers.

B. Experiments Had Headers Only, Not Other Impacts Like Kicks

An important task in automating our system is being able to automatically isolate impacts of interest (headers) from other events, such as kicks or ground hits that may be recorded by the ball. To assess this possibility, we examine and compare impacts from headers and a variety of other sources including

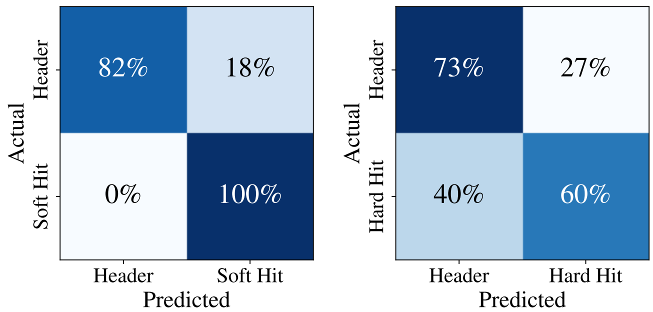

Fig. 19. Classifier results for separating headers from (a) soft and (b) hard impacts. Accuracy diminishes with the hardness of the impact.

stationary and nonstationary kicks to both falling and rolling balls. We observe that the main differentiating factor in these events is the softness of the collision surface. Softer surfaces, such as the ground or the top of a players shoe, yield impacts of larger duration which are characterized by wide initial peaks and quickly damped oscillations. Harder surfaces, such as a head or the side of a shoe, experience a narrower first peak followed by underdamped subsequent oscillations. In our experiments, we notice high accuracies for differentiating impacts in the former category, with significantly lower accuracies in differentiating between headers and hard kicks (Fig. 19).

The above-mentioned results indicate that the micoach ball alone may not be able to isolate headers from other hard impacts. However, sensors attached to shoes [8] can complement the smartball to provide an inexpensive and unobtrusive way to categorize individual impacts and hazardous headers. As is, the ability to provide a measure of the impact on the case of intentional or unintentional headers can still be of great value to the personnel watching players from the sidelines.

C. Influence of Gravity is Not Accounted for in Our Analysis

Although it is feasible that future generations of smart soccer balls will incorporate the use of a triaxial gyroscope, it is reasonable to ask how we cope with the lack of this sensor in our current experiments with the micoach ball. Specifically, without the corresponding gyroscopic information, it is impossible to remove any gravitational components in an acceleration signal. It is important to note that in our application, there is only such a component in a very limited subset of our measurement data, namely, the portion of the data that corresponds to the actual moment of contact with a players head. These impacts typically last less than 10 ms. Acceleration values outside this range, when the ball is in free fall, are free from this component due to the nature of the sensor [19]. In this paper, we simply ignore this gravitational component for lack of a better alternative. Several observations indicate that this approach is not unsound. First, our header events typically experience peak accelerations beyond 150 g, with average values measured over the impact on the 6–14 g range. These values are large enough so as to nearly make negligible the 1-g component of gravity that may be present in the brief impact period. Second, our machine learning-based approach can take this component into account implicitly, due to its presence in all training and testing data. Because we simply use derived features for making predictions rather than processing directly on the raw signal, we believe that the algorithm can learn the appropriate decision boundaries from the data itself.

VI. Ongoing and Future Work

Our experimental results show that the proposed approach of using smartball to assess header impacts has 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 data set. 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 impairment to a player's head. We will investigate how the quantities measured for the dummy translate to a real player. We are currently seeking Institutional Review Board 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 player's brain is our long-term research objective.

VII. Conclusion

The increased awareness of the harmful effects on the brain incurred from heading the ball in soccer makes impact monitoring devices essential. Existing intraoral and head-mounted sensors inconvenience players and may not be affordable for millions of amateur players. In this paper, we take a step toward eliminating the need for such devices, by showing that a smartball, embedded with appropriate sensors, holds promise in approximating the performance of an xPatch that is worn behind the player's ear. However, before we can claim that the proposed approach can be an effective alternative to head-mounted sensors, we need to address its limitations in isolating headers from the other impacts and also conduct extensive experiments during games and evaluate how well it works on real players.

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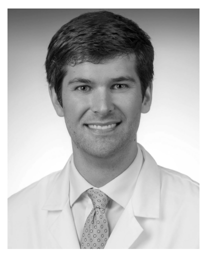

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