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Field evaluation of a small form-factor head impact sensor for use in soccer.

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Abstract

Concussions in un-helmeted sport are diagnosed at rates comparable to helmeted, but head impacts during un-helmeted play are comparatively understudied. This is due in part to the technological challenges associated with measuring head acceleration during play, but recently small form factor impact sensors have been developed to characterize impacts during participation in un-helmeted sport. This work considers the accuracy of one such sensor in identifying impacts during play. The sensor was attached to the skin over the mastoid process on 8 male high school soccer players who participated in 7 games. Video of the games was captured using four cameras recording at 60 frames per second. Sensor data were synchronized with video recordings, and each impact identified by the sensor in which peak linear acceleration exceeded 10 g was reviewed. Impacts were categorized based on the context of the contact: player contact with the ball, another player or the ground; no noticeable impact on the video but substantial player movement (e.g., deceleration, planting, turning); or no noticeable impact or change in movement (deemed false positive). Sensor accuracy was assessed by quantifying false positive identification by the sensor. Over the course of 7 games, 125 impacts were recorded. Contact with the ball was the most common mode of head acceleration and accounted for 42.4% of recorded impacts. Contact with another player accounted for 16.8% of impacts, and contact with the ground accounted for 5.6% of impacts. 4% of recorded impacts did not have contact with ball, player or ground, but did have substantial player movement noted on video. Review of the video indicated another 39 (31.2%) impacts were spurious (no contact or change in movement). Additional filter elements reduced the proportion of false positives to 13.3%, but eliminated 34 valid impacts. False positive impact magnitudes ranged from 10.0 to 31.5g, indicating that waveform analysis rather than increased thresholds may be required to improve accuracy.

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Keywords:

1. Introduction

Compared to helmeted sport, head impact exposure in un-helmeted sport is understudied despite large numbers of participants in each. In the United States approximately 1.2 million high school and college students participated in organized American football during the 2013-2014 season, while approximately 1 million students participated in basketball and 850,000 in soccer during the 2014-2015 season [1, 2]. Concussion rates (concussions per game or practice) in these un-helmeted sports were comparable to American football; collegiate women's soccer had a concussion rate that was 94% of the concussion rate in American football [3], whereas the concussion rate for high school boys basketball was 26% of the rate in American football [4]. Because of the high rate of participation in un-helmeted sports, and the risk of concussion associated with play, there is a need to better characterize head impact exposure for these sports.

Several sensor systems have been developed to quantify head impact exposure in an effort to better understand the mechanisms of sport-related concussion. One of the most widely used devices is the Head Impact Telemetry System, or HITS, which houses the sensors within the helmet assembly [5–8]. Because systems like these require a helmet, a wide variety of head

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impact sensors have recently been developed to be used in un-helmeted sport. These devices have been designed to attach to the head using adhesives, straps, headbands, embedded within mouthguards or inserted into the ear canal [9–12].

Attempts to validate head impact sensor accuracy in identifying impacts of interest and spurious impacts is limited due to the lack of a standard for measuring head acceleration *in-vivo*. Un-helmeted sport, however, offers a substantial advantage over helmeted sport because there is no helmet to obscure observations of interaction between participants and the play environment. The attachment of sensors to the head in unhelmeted sport is also more intimate than the attachment of a helmet to the head. This work considers the impact identification performance of a small form factor, wireless head impact sensor representative of those used for un-helmeted sport. Video recordings of soccer games were used to evaluate the ability of the sensor system to identify valid and spurious impacts.

2. Methods

2.1. Subjects

On-field head impact measures were obtained from eight high school aged male subjects over the course of a single season of high school soccer. Approval for this study was obtained from the Institutional Review Board at Washington State University; assent and informed permission was obtained from participants and their legal guardians prior to participation in the study.

2.2. Data Collection

Measurements of linear and angular acceleration were obtained using the xPatch device (Figure 1; X2 Biosystems, Seattle, WA). The xPatch used a combination of accelerometers and gyroscopes to measure three dimensional linear angular velocities in a small form factor, allowing the devices to be worn on the soccer field. Linear acceleration and angular velocity data was collected at 1kHz and approximately 800Hz, respectively. These data were processed using proprietary algorithms to classify impacts as impacts predicted valid (PV) or predicted spurious (PS), and determine peak linear and peak angular accelerations for each impact. A double-sided adhesive provided by the manufacturer was used to attach the sensor over the mastoid process of each subject prior to play. Impacts having a peak linear acceleration greater than 10g were recorded for analysis, as done elsewhere [5, 13].

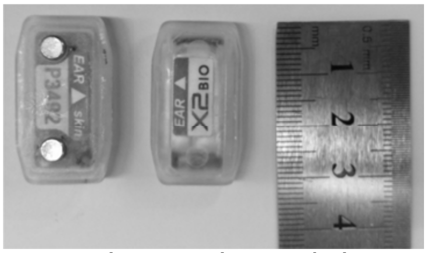


Figure 1. Wireless sensor used to measure head impacts during un-helmeted play.

Subjects played in seven soccer games over the course of a regular season. Each game was taped using four video cameras recording at 60 frames per second and 1080p resolution. Video was synchronized with head impacts sensors prior to the start of each game by mounting the sensors worn by the players and a reference sensor onto a stiff board. The board was struck, causing each sensor to record an impact. These data were used to map individual sensor times to the reference sensor time. The reference sensor was then impacted in view of the cameras, and the reference sensor time mapped to video time. In this way, the time of impacts recorded by each sensor was determined with respect to the collected video.

2.3. Data Analysis

Two levels of post-processing were used to identify spurious impacts based on linear and angular acceleration data. In the first round of analysis, a proprietary cross-correlation method was used to identify PV impacts based on a range of previously identified waveform characteristics. In the second round, high-pass filtering was conducted to address sensor drift and a proprietary “running filter” used to remove PS impacts resulting from ground reaction forces during running were used in addition to the cross-correlation algorithm.

For each level of post-processing, impacts classified as PV by the head impact sensors were identified in the collected video based on time code and player number. Impacts were considered actually valid (AV) if contact was observed in the video between the subject and the ball, another player, the ground or if the player was engaged in substantial motion (e.g., striking the ball, sudden change of direction, etc.). Impacts not associated with contact or substantial motion upon review of the video were classified as actually spurious (AS). Accuracy of the sensor system was assessed by quantifying the proportion of false positive impact classifications, or the rate at which AS impacts were identified as PV.

Video data was independently reviewed by two researchers and Cohen's kappa was calculated to assess inter-rater reliability of impact categorization. Kruskal-Wallis one-way analysis of variance and post-hoc Dunn's tests were used to compare linear and angular impact acceleration category (ball contact, other player, ground contact, player motion, spurious) for each post-processing method separately.

3. Results

Over the course of the seven games observed, 125 impacts greater than 10g and classified as PV using the cross-correlation post-processing algorithm were recorded. Each of these impacts were categorized and inter-rater reliability analysis found a Kappa of 0.85 ($p < 0.05$; 95% CI: 0.78, 0.93) indicating very good agreement between the two reviewers. After the second round of post-processing 60 impacts were identified as PV. Agreement between video reviewers remained high for this subgroup analysis (Kappa of 0.85, $p < 0.05$; 95% CI: 0.72, 0.98).

Using only the cross-correlation post-processing algorithm, the most common mode of head acceleration was contact with the ball, which accounted for 42% of impacts, and the least common mode was player motion, accounting for 4% of reviewed impacts. The most and least common modes were the same for impacts classified as PV by the second post-processing method, with 67% and 2% of impacts resulting from contact with the ball and player motion, respectively (Figure 2). Review of all impacts indicated that the second post-processing method reduced the proportion of spurious impacts to 13% from 31% for the cross-correlation method. The additional post-processing also removed 13 impacts from both ball and other players impact categories, and 4 impacts from each of ground contact and player motion (Figure 2).

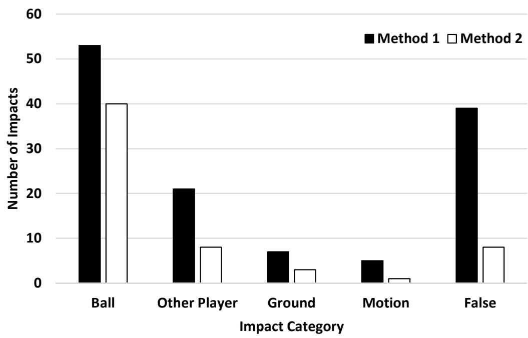


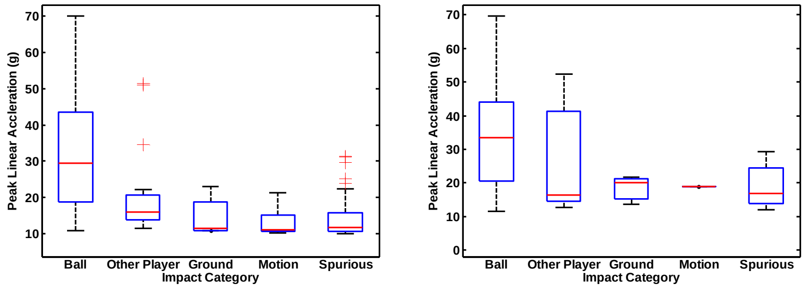
Figure 2. Number of impacts identified by both post-processing methods in each category based on video review.

For the cross-correlation post-processing method, contact with the ball produced the largest head impact magnitudes and player motion produced the lowest magnitude impacts. Of PV impacts identified using the second post-processing method, contact with the ball resulted in the largest impact magnitudes and contact with other players resulted in the lowest (Table 1; Figure 3; Figure4).

Table 1. Median and range of peak linear and peak angular acceleration measured over the course of the season for each impact category.

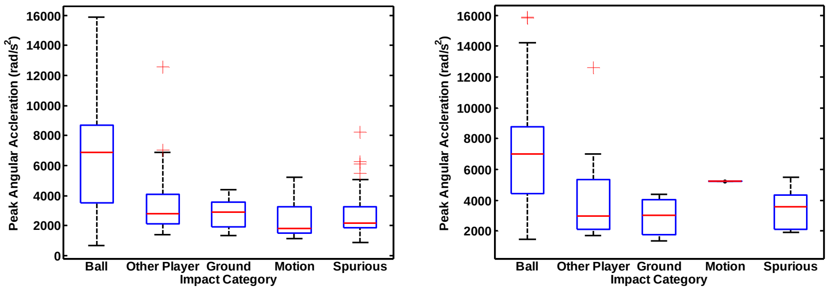
Contact Mode	Peak Linear Acceleration (g) (median; [range])		Peak Angular Acceleration (rad/s^2) (median; [range])	
	Method 1	Method 2	Method 1	Method 2
Ball	29.4 [10.9 – 69.9]	33.5 [11.6 – 69.6]	6,892 [653 – 15,864]	7,003 [1,457 – 15,864]
Other Player	16.0 [11.5 – 51.4]	16.31 [12.8 – 52.5]	2,780 [1,386 – 12,583]	2,982 [1,689 – 12,583]
Ground	11.6 [10.9 – 23.1]	20.1 [13.7 – 21.7]	2,889 [1,352 – 4,379]	3,025 [1,352 – 4,379]
Motion	11.1 [10.3 – 21.3]	19.0 [19.0 – 19.0]	1,806 [1,129 – 5,239]	5,239 [5,239 – 5,239]
Spurious	11.7 [10.0 – 31.5]	16.8 [12.1 – 29.2]	2,187 [856 – 8,225]	3,566 [1,910 – 5,473]

Kruskal-Wallis analysis of variance and post-hoc Dunn's tests did not show a significant difference between impact categories for impacts identified with the second post-processing method. For impacts identified using the first post-processing method, significant differences in linear acceleration magnitudes were observed between ball impacts and ground, motion and spurious impact categories (X^2= 52.6, p < 0.01; Q = 2.80). Likewise, significant differences were also observed for angular acceleration magnitudes between ball impacts and motion and spurious impact categories (X^2= 43.5, p < 0.01; Q = 2.80) for impacts identified using the first post-processing method.



(A) (B)

Figure 3. Distribution of peak linear accelerations observed for predicted valid impacts as identified using the cross-correlation (A) and secondary post-processing method (B).



(A) (B)

Figure 4. Distribution of peak angular accelerations observed for predicted valid impacts as identified using the cross-correlation (A) and secondary post-processing method (B).

4. Discussion

This work investigated the performance of a wireless head impact sensor in conjunction with two post-processing methods in identifying head impacts during soccer games. Video of each game was collected and used to categorize each impact identified by the sensor system. Impacts were categorized by two reviewers who demonstrated good agreement in inter-rater reliability analysis, which suggests that the categorization scheme was well defined enough to result in consistency.

This study examined sensor performance by comparing impact classification based on head impact data to video review of the games wherein the head impacts were recorded. Video analysis is an imperfect tool for this purpose, and as a result of its use we were unable to measure the total number of impacts that occurred during play, and therefore unable to measure the false positive rate or the specificity of the system.

Based on measurements from the wireless sensor, head accelerations resulting from contact with the ball were found to be significantly larger than impact magnitudes of all other categories, including spurious impacts. This suggests that inclusion of spurious impacts is unlikely to cause over estimation of peak impact magnitudes, but may skew the data set to lower impact magnitudes and lead to an underestimation of head impact exposure over the monitored period. Additionally, the absence of a statistically significant difference between AS and AV impact magnitudes suggests that correct classification of impacts will likely need to rely on waveform analysis to identify AV impacts.

Using the cross-correlation post-processing method, 125 impacts were identified of which 86 (69%) were determined to be AV upon review of game video. Addition of a high-pass filter to address drift and a proprietary “running” filter removed 65 impacts, of which 34 were AV and 31 were AS. This resulted in a data set of 60 impacts containing 52 AV impacts (87%). The false discovery rate of the sensor, particularly when using only the cross-correlation post-processing method, was not negligible. Additional filter elements (the high-pass filter and “running” filter) decreased the proportion of AS to AV impacts in the dataset, but at the expense of removing AV impacts. These results indicate that video review will likely be necessary to appropriately interpret data collected with this device until more effective waveform analysis tools are available.

5. Acknowledgements

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