Video assessment of head impact exposure in American football

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Abstract

Previous research has sought to quantify head impact exposure using wearable kinematic sensors. However, validation studies have shown that most sensors suffer from poor accuracy in estimating impact severity and count, motivating the need for additional independent impact exposure quantification. Here, we implemented a tiered video assessment to collect American football head impact exposure data. We also developed a new exposure metric unique to American football quantifying number of impacts per player-play, and found significantly higher exposure during games (0.40, 95% CI: 0.33-0.47) than practices (0.26, 95% CI: 0.23-0.30) ($p<0.05$). Using the more traditional impacts per player-hour metric, we observed higher exposure during practices (4.7) than games (3.6) due to the greater number of player-plays per hour (17.8 practices vs. 9.1 games). Thus, our exposure metric accounts for variability in on-field participation, providing more accurate depictions of impact likelihood when in play. We further coupled our video assessment with an instrumented mouthguard, and found median impact linear acceleration angular velocity, and angular acceleration magnitudes of 19.0g, 9.9rad/s, and 1358.8rad/s^2 respectively during practices, and more severe 23.7g, 13.4rad/s, and 1483.5rad/s^2 respectively during games ($p<0.5$ in linear acceleration magnitude). Our results agree with previous findings showing higher exposure and more severe impacts during games. However, our impact directionality results differed substantially, with 1.5% identified as rear impacts in video assessment, and 30.9% identified as rear impacts in previous sensor-based exposure studies. This discrepancy demonstrates the need for collecting independent, unbiased impact exposure data to compare against sensor-based findings.

Introduction

Concussions are a common injury in contact sports, with an estimated 300,000 sports-related concussions in the United States annually (1). Concussions lead to short-term neurological deficits (2,3), and a history of concussions have been correlated with increased risk of developing long-term neurodegeneration (4). Despite being a serious health risk, concussions are under-reported due to the qualitative nature of diagnosis (5). Thus, to improve athlete safety and health, it is imperative we understand the mechanism of concussion.

One critical step towards understanding concussion mechanisms is to quantify the exposure of athletes to potentially injurious head impacts. Many studies have found that athletes may be more susceptible to sustaining a concussion depending on their exposure to head impacts (6,7), and more recent studies have suggested that exposure to repeat subconcussive head impacts over a career could also increase risk of long-term neurodegeneration (8,9).

To quantify head impact exposure to athletes on the field, previous studies have focused on instrumenting American football athletes with wearable sensors (6,10–20) (Table 1). These sensors have proven useful in collecting both head impact count and the kinematics of head impacts from a large number of players. In particular, the Head Impact Telemetry System (HITS) (21,22) has been used extensively to collect data on hundreds of thousands of impacts over the past decade, and exposure data collected from these studies have been used to define injury thresholds and develop helmet testing protocols (23).

Table 1: Previous exposure studies

Previous Study	Team	Seasons	Sensor	Additional Impact Verification	Impact Count	Impact Severity
Beckwith et. al. [6]	NCAA Div. 1 HS Varsity	2005 – 2010	HITS	Exclude <10g peak linear acceleration Exclude impacts outside event time Exclude non-head impacts	14.7 impacts per event for concussed players	20.7g median, days without concussion 22.5g median, days with concussion
Brolinson et. al. [10]	NCAA Div. 1	2003 – 2004	HITS	10g impact threshold	>7.2 impacts per event*	15.3g median
Broglio et. al. [11]	HS Varsity	2007	HITS	15g impact threshold Questioned athletes severe impacts	15.9 impacts per event	24.8g mean during games 23.3g mean during practices
Crisco et. al. [12]	NCAA Div. 1	2007 – 2009	HITS	Exclude <10g peak linear acceleration Rigid-body modeling Video correlation of impacts >125g	6.3 impacts per practice 14.3 impacts per game	20.5g median
Duma et. al. [14]	NCAA Div. 1	2003	HITS	10g impact threshold Video correlation of impacts	>15.0 impacts per game* >7.6 impacts per practice*	32g mean
Kawara et. al. [15]	NCAA Div. 1	2015	i1 Mouthguard	10g impact threshold	7.0 impacts per event	30.3g mean
Mihalik et. al. [16]	NCAA Div. 1	2010	HITS	Exclude <10g peak linear acceleration Video correlation of impacts**	14.4 impacts per game	24.7g mean in anticipated impacts** 27.0g mean in unanticipated impacts**
Mihalik et. al. 2 [17]	NCAA Div. 1	2005 – 2006	HITS	Exclude <10g peak linear acceleration Exclude impacts outside event time	57,024 impacts from 72 players over two seasons	22.7g mean in full contact practice 21.1g mean in games
Naunheim et. al. [18]	HS Varsity	Not Reported	Linear Accels in Helmet	10g impact threshold Video correlation of impacts	40.5 impacts per player-hour during game	29.2g mean
Reynolds et. al. [20]	NCAA Div. 1	2013	x2 Skin Patch	10g impact threshold Proprietary false impact filter Exclude impacts outside event time	24.2 impacts per game 16.8 impacts per full pad practice	28.2g mean during games 28.8 mean during full pad practices
Shnebel et. al. [19]	NCAA Div. 1 HS Varsity	2005	HITS	10g impact threshold	>12.9 impacts per event, college* >21.7 impacts per event, HS*	58.8g 95th percentile, college 56.2g 95th percentile, high school

HS = high school
* Papers state impacts per event with at most some number of players equipped in an event. Impact count is calculated assuming all players equipped, but this is not necessarily true and is not reported.

** Mihalik et. al. [16] only performs video analysis on a subset of impacts collected and does severity statistics on the subset.

However, recent studies have shown that HITS, and many other wearable sensor systems, may suffer from poor accuracy in both classifying head impacts (impact count) (24–26), and measuring head impact kinematics (impact severity) (22,27–29). This raises questions about the validity of previously collected, sensor-based head impact exposure data, and motivates the need for an independent methodology for collecting impact exposure data.

Video assessment represents an option for collecting a dataset of head impact exposure. Video assessment has been used extensively to review plays and sports injuries by coaches and medical professionals (30–34). Several sensor-based exposure papers also use video assessment to confirm sensor recorded impacts; however they only view videos of sensor identified impacts (12–14,17,18). As a result, current methodologies assume that sensors are capable of detecting all head impact instances and only evaluate sensor precision, and do not correct for false negatives in impact detection.

In this work, we introduce a video assessment protocol to collect a video-based head impact exposure dataset in collegiate American football. We pair this video assessment with an instrumented mouthguard (24,28,35,36), which collects data on impact kinematics. Finally, we introduce a new exposure metric for quantifying head impact exposure unique to American football, which measures the number of head impacts sustained over a single player-play. While traditionally, exposure is quantified as the number of impacts per athlete exposure (defined as an athlete participating in a practice or game), American football is a unique sport where every player is expected to spend varying amounts of time on the field and in play. As an example, statistics on National Football League games report average of 133.6 plays per game, of which 10.3 involve punting. Thus, specialized players such as punters are on the field, and thus exposed, far less often than players such as linemen. Our exposure metric accounts for variability in on-field participation, and normalizes exposure by the base unit for American football: a single play.

Methods

To collect a video-based head impact exposure dataset, we relied on a tiered video assessment protocol. Impact severity was also measured using the instrumented mouthguard, with impacts being identified first in video, rather than using the sensor directly.

Deployment and Instrumentation

Data were collected from the Stanford University American football team during the 2015 fall season. Seven players were consented for study participation through the Stanford Internal Review Board IRB #34943. Players represented a variety of positions (three offensive linemen, one running back, one fullback, one wide receiver, and one defensive linebacker).

Players wore instrumented mouthguards (35,36) (Fig 1) for the entire fall season in all practices and games. Before the 2015 fall season, we collected upper dentition impressions from our seven consented players. Electronic boards containing kinematic sensors, flash memory, and processing were embedded between two layers of 3mm ethylene vinyl acetate, which were pressure formed against the dentitions.

Fig 1. Instrumented mouthguard for measuring impact severity. (A) Sensor board containing tri-axial linear accelerometer and tri-axial angular gyroscope are embedded (B) inside a custom-formed instrumented mouthguard.

The electronic boards contained a tri-axial linear accelerometer (H3LIS331) and tri-axial gyroscope (ITG3701A), both sampling at 1000Hz. The linear acceleration data were filtered at CFC180 (300Hz fourth order Butterworth low pass filter) (37) while the angular velocity data were filtered with a 184Hz fourth order Butterworth low pass filter (manufacturer defined bandwidth). Impacts were identified using a 10g linear acceleration magnitude threshold, and data were collected 10ms before and 90ms after impact

trigger. The mouthguard was designed to last 3.5 hours and collect up to 1638 impacts. While the primary purpose of this work was to collect an independent video-based exposure dataset for comparison against sensor-based exposure statistics, the dataset is also being used to develop a robust impact detection algorithm for the instrumented mouthguard.

Impacts collected on the instrumented mouthguards were time stamped based on an internal real-time clock to within one second. Internal clocks were synchronized to the National Institute of Standards and Technology time (nist.time.gov) prior to an event. A unique “time-sync” mouthguard not built for any players was used to synchronize mouthguard times with the camera times for impact correlation. This was accomplished by having an athletic trainer apply known impacts on the “time-sync” mouthguard in view of all cameras. The real-time stamps on the “time-sync” mouthguard were matched with those on the cameras after the event.

Video Assessment Overview

The video assessment protocol was designed to be both rigorous and efficient. We utilized multi-angle video to better view players on the field, and a tiered assessment method for both sensitive and specific identification of activities, most notably head impacts (Fig 2).

Fig 2. Overview of tiered video assessment for collecting head impact exposure dataset. (A) Multiple video angles were collected for each practice and game, with at least one camera capturing an end-zone view and one camera capturing a sideline view. (B) Video was trimmed by technicians to only include play footage. (C) Trained raters performed a first round of video assessment, tracking specific players and labeling their activity. (D) A second round of video assessment performed by one of the authors confirmed Helmet Contact activities.

Video was first collected during practices and games from multiple viewing angles using 1080p resolution cameras recording at 30fps. We obtained two videos per field, with one video taken from the end-zone

and another taken from the sideline. Because practices utilized multiple fields, there were four videos per practice, and two videos per game.

Next, videos were trimmed to only include plays, which cut video time in half. Then, in a first round of video assessment, several trained raters were tasked with tracking single players in each video, and tagging their activity. In this first round of video assessment review, raters were instructed to be sensitive to Helmet Contact activities. Finally, one of the authors, who had over three years of experience deploying wearable sensors and evaluating video footage, performed a second round of video assessment of all identified periods of Helmet Contact. The author viewed periods of Helmet Contact from multiple angles with the purpose of being specific in identifying Helmet Contact activities.

Video Assessment First Round

During the first round of video assessment, raters were tasked with tracking single players in all videos associated with an event, and labeling their activity. A total of fourteen raters were trained to classify player actions in the videos.

We classified player activity with six distinct labels: Helmet Contact, Body Contact, No Contact, Obstructed View, Idle, and Not in Video (Fig 3). We defined Helmet Contact activity as any continuous period with direct contact to the tracked player's helmet, and Body Contact as any continuous period with contact elsewhere on the body. While Body Contact could induce head accelerations through whiplash effects, they were not considered head impacts in this analysis. No Contact events were classified whenever players were observed on the field, participating in a play, but not in contact with anyone or anything. Obstructed View events were used whenever a player exited camera view, such as when a player was tackled by multiple opponents and could not be seen. Idle events were classified whenever a tracked player was observed in video, but not on the field participating in the play. This was most commonly observed when the player was on the sideline. Finally, Not in Video events occurred when a player was not visible in any video.

Fig 3. Activity classifications for tracking player activity and identifying Helmet Contact activities with high sensitivity. Tracked player marked with a red arrow. (A) Raters identified Helmet Contact activities whenever the tracked player's head overlapped with an opposing player. (B) Body Contact activities when there was contact not involving the head. (C) No Contact activities when player was in play, but not actively in contact. (D) Obstructed View activities when there was no clear view of the player's head. (E) Idle activities when players were observed on the sideline, or otherwise not in play. Finally, (F) Not in Video activities when tracked player was not in the video.

For the purposes of this study, we asked raters to be particularly sensitive to identifying Helmet Contact activities. Helmet Contact activities were tagged whenever the tracked player's helmet overlapped with another player or object in video. Additionally, multiple Helmet Contact activities were tagged when there were potentially multiple independent helmet impacts in quick succession. This provided an upper bound on the number of Helmet Contact activities sustained.

Due to the large number of videos, each video was only viewed by one rater. Thus, it was necessary to train raters to classify player actions consistently, and assess rater reliability. Because we instructed raters to be sensitive to Helmet Contact events, we assessed raters on their reliability in identifying Helmet Contact Events. First, raters were trained on a 2-minute demonstration video that explained activity classifications. Next, raters were evaluated on a 10-minute video to ensure good rater reliability. Both training and evaluation video clips were taken from videos collected as part of this study. Rater reliability was assessed by comparing the number of Helmet Contact events classified by each rater in the 10-minute evaluation video to the number of Helmet Contact events classified by the author performing a second round assessment. The fourteen raters classified an average of 88% of the Helmet Contact events identified by the second round assessment author.

Video Assessment Second Round

After raters classified player actions within the videos, the author with over three years of experience deploying wearable sensors and analyzing video footage performed a more detailed analysis for specific

identification of Helmet Contact activities. Because Helmet Contact represents potential impacts to the head and exposure to injury, it was necessary to perform a more detailed breakdown to confirm a Helmet Contact activity, and obtain qualitative information such as contact location and directionality.

For each rater identified Helmet Contact activity, one author reviewed all video angles to confirm Helmet Contact activity (Fig. 4). Observed Helmet Contact activities were then further classified by contact location to the player (helmet front, side, top, rear and their combinations), and contact location on the opponent (helmet, body, upper limb, lower limb, and ground).

Fig 4. Second round video assessment for specific Helmet Contact activity identification. Multiple videos were used to confirm Helmet Contact activities. Red arrows mark the tracked player, with blue arrows marking other players. End-zone videos show helmet overlap, but sideline video showed (A) definitive head contact and (B) no helmet contact.

Analysis

From this tiered video assessment protocol, we were able to collect head impact exposure data. Helmet Contact activities were compiled after the second round of video assessment. The video time stamps for the Helmet Contact activities were then used to identify mouthguard triggers associated with these periods of contact, which represented discrete head impact events. This differs from previous analysis in that we used video to find impacts, and subsequently identified them in the mouthguard sensor. This allowed us to assess sensor impact detection sensitivity. Previous studies relied on sensors to identify impacts, and then confirmed them in video, which limits assessment to impact detection precision (25,26).

The data from the instrumented mouthguard was used to assess the severity of the identified impacts. We computed the peak linear acceleration, angular velocity, and angular acceleration magnitude from each impact identified by the mouthguard. In addition, we used the sensor's linear acceleration measurement to bin the impact based on direction. We defined location vectors at front (1, 0, 0), rear (-1, 0, 0), side (0, ±1, 0), oblique (±1, ±1, 0), and top (0, 0, 1). We then took the linear acceleration vector at

peak magnitude, and defined the sensor-based impact location as occurring in the opposite direction (an impact to the front of the head causes acceleration towards the rear of the head). The impact was binned by finding the location vector with the smallest angle with respect to the sensor-based impact location. We compared the resulting sensor-binned impact location against those found during the second round of video assessment.

We computed several exposure metrics for the purpose of this study. The first exposure metric was the number of head impacts per player-hour. To compute this, we found the number of head impacts, and the number of hours of play recorded by the mouthguard.

The second exposure metric was the number of head impacts per player-play. A player-play was identified based on the player activity timeline combined from all videos during an event. Helmet Contact, Body Contact, and No Contact activities were associated with players in play, and the Idle and Not in Video activities were associated with players not in play. Sequences of Helmet Contact, Body Contact, and No Contact activities were represented by a single play. The final exposure metric we computed was the number of plays per player-hour.

Results

Fourteen raters reviewed over 163 hours of video for the seven players spanning 11 practices and 6 games during the 2015 fall season. This represented over 62 hours of mouthguard recordings. In that time, players participated in 927 plays. Raters identified 1004 Helmet Contact activities after first round video assessment, of which 271 were confirmed following second round video assessment. Of those, 193 were recorded by the instrumented mouthguard, representing a sensor sensitivity of 71.2%, if video-assessed impact count is treated as the ground truth measurement.

Impact Exposure

Here, we further delineate video-based impact exposure based on event type (games or practices) and player position (Fig 5). Results show that exposure defined in terms of impacts per player-hour differ than what has been previously found. All players except the linebacker had a greater number of head impacts per player-hour in practices than in games. When considering the number of impacts per player-play however, we found that most players sustained more impacts per player-play during games than during practices. Indeed overall, players experienced significantly fewer impacts per player-play during practices (0.26, 95% CI: 0.23-0.30) than during games (0.40, 95% CI: 0.33-0.47) ($p<0.05$). This discrepancy is likely due to a difference in amount of play seen, where all players participated in significantly more player-plays per player-hour in practices (17.8, 95% CI: 16.5-19.1) than in games (9.1, 95% CI: 7.9-10.5) ($p<0.05$).

Fig 5. Impact Exposure Statistics Comparing Exposure Metric to Traditional Metrics. (A) Players generally experienced more impacts per player-play during games than during practices (* $p<0.05$, ** $p<0.01$), with linemen having the statistically highest ($p<0.05$) head impact exposure in both games and practices. In contrast, (B) all players except the linebacker experienced more impacts per player-hour in practices than in games. This is likely because (C) all players participated in significantly more player-plays per player-hour in practice than in games. This discrepancy skewed exposure statistics that were normalized by player-hour.

We also observe differences in exposure between player positions. Linemen had significantly higher exposure to head impacts per player-play ($p<0.05$), with a head impact occurring in more than one of every two plays. The fullback and linebacker had the next highest exposure, with the running back and wide receiver having the lowest exposure, both sustaining less than one impact in every ten plays.

Impact Severity

Impact severity was only quantified in the 193 impacts recorded by the instrumented mouthguard. We delineate impact severity based on event (games or practices) and player position. Peak impact kinematics distributions are shown for games and practices (Fig 6), with player positions individually

represented. Over all player positions, the median peak linear acceleration, angular velocity, and angular acceleration magnitude was 19.0g (95% CI: 17.4-20.8g), 9.9rad/s (95% CI: 9.1rad/s-10.7rad/s), and 1358.8rad/s^2 (95% CI: 1173.6rad/s^2-1534.0rad/s^2) respectively during practices, and 23.7g (95% CI: 21.6-26.6g), 13.4rad/s (95% CI: 10.9rad/s-14.9rad/s), and 1483.5rad/s^2 (95% CI: 1354.8rad/s^2-1729.0rad/s^2) respectively during games. While the medians were larger during games, only peak linear acceleration magnitude had a significant difference ($p<0.05$).

Fig 6. Impact severity distribution during practices and games. (A) Peak linear acceleration magnitude distribution, (B) peak angular velocity magnitude distribution, and (C) peak angular acceleration magnitude distribution of impacts for each player position in games and practices. Data are fit with a lognormal distribution. Median and interquartile range kinematic values are lower for practices than for games. While the wide receiver position had observed impacts, there were no recorded impacts (possibly because impacts were below the 10g threshold) and the wide receiver position is not included here.

Impact Location

Finally, we quantified the distribution of impact locations in our dataset, based both on the second round video assessment and mouthguard kinematics (Fig 7). In both cases, the majority of impacts occurred to the front, front oblique, and sides of the head respectively. 40.5%, 23.1%, and 30.3% of impacts were observed in video assessment in the front, front oblique, and sides of the head for a total of 93.8% of impacts. According to mouthguard kinematics, 32.3%, 34.9%, and 13.4% of impacts occurred to the front, front oblique, and sides of the head respectively for a total of 80.7% of impacts.

Fig 7. Impact locations demonstrate majority of impacts to front and side. (A) Locations are binned into front, front oblique, side, rear oblique, rear, and top impacts. (B) Impact locations as classified during second round video assessment. (C) Impact location as classified based on instrumented mouthguard linear acceleration. In both cases, the majority of impacts occur to the front, front oblique, and side locations.

When comparing the location determined through video with the location determined using the mouthguard kinematics, we found that the mouthguard only predicted impact location correctly in 63 of 193 impacts (32.6%). We also quantified head impacts based on the opposing impact object (opposing helmet, body, limb, or ground), and found 64% were to an opponent's helmet, 27% were to an opponent's body, 5% were to an opponent's upper or lower limbs, 3% were to the ground, and 1% were to other objects such as practice pads.

Discussion

In this work, we present a tiered video assessment protocol for obtaining an independent video-based dataset for head impact exposure in American football to compare against sensor-based impact exposure statistics. The video-based exposure dataset also provides additional exposure information such as the impacting object (64% opposing helmet). This work differs from previous head impact exposure datasets that rely primarily on imperfect head impact sensors, and then confirm true positive vs. false positive head impacts in video. Here, we first identified Helmet Contact activities in video to identify impacts recorded by an instrumented mouthguard, which allows us to also assess the sensitivity of wearable sensors in identifying head impacts (e.g. false negatives). In addition, we also introduce a new American football specific exposure metric based on the number of head impacts per player-play, which account for players varied involvement during events.

To demonstrate the advantage of collecting head impact exposure using the video assessment protocol, we highlight two key differences between the video expoure dataset and a wearable sensor exposure dataset (obtained using an instrumented mouthguard).

First, we note that the instrumented mouthguard only detected 71.2% of the video classified Helmet Contact events, missing 76 of 271 events. One possible reason for this is that the instrumented mouthguard was set to record an impact event when the linear acceleration magnitude exceeded 10g, which is similar to impact thresholds employed in previous work (Table 1). In video assessment however,

Helmet Contact events were identified by observing physical contact of the helmet with another object, not accounting for the severity of the contact. Thus, observed Helmet Contact events could have linear accelerations below the 10g sensor threshold. In fact, 81% of unrecorded impacts were noted as “light severity” or involved body or facemask impacts.

Previously, the 10g sensor threshold was chosen to differentiate head impacts from other events resulting in head motion, such as jumping or running (38). But, as researchers are suggesting multiple mild impacts could have implications on brain injury risk and long-term degeneration, it is becoming increasingly important to identify any head impacts, regardless of severity. Furthermore, recent literature has moved towards using a 20g linear acceleration magnitude threshold to deal with occurrences of false positives, but moving to a 20g threshold would result in a loss of an additional 103 head impacts from our dataset, resulting in a sensitivity of 34.0%. This agrees with previous literature investigating the importance of the linear acceleration threshold in identifying impacts (38).

Second, vide assessment is especially valuable for visually confirming impact location estimates. In video, we found that 93.8% of impacts occurred to the front, front oblique, and side of the head after the second round of video assessment. The instrumented mouthguard found similar trends for impact location with 80.7% of impacts occurring in the front, front oblique, and side locations; however, the mouthguard impact location matched video identified impact location less than one third of the time. This could be the result of decoupling between impact location observed in video, and head motion as predicted by the mouthguard. In a direct impact, the impact location is expected to correspond with the direction of motion, however we note that our raters observed impacts in which helmets “slid past one another”, resulting in impact locations that do not necessarily correspond to the measured direction of motion.

Another possible reason for the discrepancy is the assumption that the peak linear acceleration direction corresponds to the impact location for the mouthguard direction analysis. Due to the complexities of the human head-neck system and the unpredictable dynamics of impacts, there may not be a strong

correlation between impact location, and the resulting peak linear acceleration vector. Better algorithms that utilize the time history of head impact motion may fare better at predicting impact location.

In addition to discrepancies in head impact location between video assessment and our instrumented mouthguard sensor, our observed distribution of head impact locations differs with previously reported impact location distributions, which report up to 31.9% of impacts to the rear of the head (39). The discrepancy in impact location distributions may be a result of inaccuracies of previous head impact sensors. From Table 1, we see that the majority of previous exposure studies rely on HITS, which has been shown in the laboratory to have kinematic inaccuracies. Of note, HITS has also been shown to misclassify impacts to the facemask as rear impacts, which may skew impact location distributions (40).

To quantify our video-based head impact exposure, we present a novel head impact exposure metric specific to American football. For our exposure metric, we look specifically at the number of impacts normalized by the number of player-plays, to account for variability in on field activity between different player positions. Schnebel et. al. alluded to head impact exposure per player-play, stating that linemen tend to have head impacts every play whereas skill players have head impacts more rarely (19). We have utilized this new metric because of the unique way in which American football is played, where players are not on the field for the entire game.

Table 2 demonstrates the power of reporting head impact exposure using the metric. First, we compare the head impact exposure of a linebacker in two separate games, in which he was observed for 90-120 minutes. In the first game, the linebacker had only 3 head impacts in 6 plays, whereas in the second game, the linebacker had 14 head impacts in 35 plays. In this example, we see that the linebacker had a near 4-fold increase in head impacts per player-hour. However, the exposure was more consistent across the two games.

Table 2: Head impacts per play exposure metric

Player ID	Game Date	Time Observed	# of Plays	# of Impacts	Impacts per Player-Hour	Impacts per Player-Play
Same Player, Different Games						

411 Linebacker	11/07/2015	1:28:52	6	3	2.0	0.50
411 Linebacker	11/21/2015	1:50:39	35	14	7.6	0.40
Different Players, Same Game						
237 Lineman	11/28/2015	1:14:00	30	20	16.2	0.67
751 Lineman	11/28/2015	1:34:25	5	3	1.9	0.60

In the second example, we observe two different linemen participating in the same game. The first lineman is a starting lineman, whereas the second lineman is only used in special packages. We see that while both players were recorded for 75-95 minutes, the starting lineman sustained many more head impacts. In terms of head impacts per player-hour, the starting lineman had a more than eight-fold increase compared with the second lineman. Again, the exposure is more consistent across the two linemen. We believe this metric of defining head impact exposure in American football prevents skewing from variable on-field participation. The metric can be further refined to discount non-contact practice drills, which would also skew exposure counts normalized by time or event.

With this exposure metric, we found that there were significantly more head impacts per player-play during games (0.40, 95% CI: 0.33-0.47) than during practices (0.26, 95% CI: 0.23-0.30). From instrumented mouthguard kinematic measurements, we found median head impact linear acceleration, angular velocity, and angular acceleration magnitude was 19.0g (95% CI: 17.4-20.8g), 9.9rad/s (95% CI: 9.1rad/s-10.7rad/s), and 1358.8rad/s^2 (95% CI: 1173.6rad/s^2-1534.0rad/s^2) respectively during practices, and 23.7g (95% CI: 21.6-26.6g), 13.4rad/s (95% CI: 10.9rad/s-14.9rad/s), and 1483.5rad/s^2 (95% CI: 1354.8rad/s^2-1729.0rad/s^2) respectively during games. Together, these results suggest that head impacts are both more frequent and more severe in games than in practices, which agrees with previous exposure data collected solely with wearable sensors.

While we successfully collected an independent video-based exposure dataset utilizing a tiered video assessment protocol, this study has several limitations. First, video assessment takes a substantial amount of time. Analyzing 160 hours of video required 1000 man-hours, primarily due to the rigor and detail required. This prevents manual video assessment from being viable for everyday use. However, this protocol can be used to collect datasets with which to evaluate sensors head impact detection, and

automated video assessment based on these protocols can be developed for a more streamlined post-event analysis (41,42). In fact, the dataset collected here is being used to develop an impact detection algorithm for the instrumented mouthguard (24).

Second, we note that there was a substantial loss of Helmet Contact events between the first and second round of video assessment (1004 Helmet Contact events following first round, 271 Helmet Contact events following second round). This was because raters were instructed to be sensitive to any potential instance of Helmet Contact, and labeled any helmet overlap with another object as a Contact event. In addition, the videos in the first round of assessment were viewed independently, with multiple video views of events only considered in the second round. Thus, in the second round of review, the majority of these events were pruned because observation of potential Helmet Contact activities in multiple video angles confirmed there was no contact between the helmet and other objects.

Third, we have shown previously that the instrumented mouthguard design can be susceptible to lower mandible disturbances, resulting in overestimation of the measured kinematics (36). Despite this, impact severity trends agree with previously reported values. Future studies will use an updated instrumented mouthguard design that mitigates these disturbances to obtain more accurate impact kinematics. The impact count data reported in this study does not rely on instrumented mouthguard kinematics, and thus are not affected by measurement errors.

Finally, we do not consider Obstructed View activities as head impacts. In some activities labeled as Obstructed View, the tracked player is taking part in a large tackle on the field, and is hidden beneath other players. This is particularly true of linemen. It is possible that we miss head impacts during these plays, and it is possible that these plays produce more impacts in under-represented locations (rear, rear oblique, and top). In our analysis, there were 29 observed instances of an Obstructed View.

In conclusion, we have developed a tiered video assessment protocol for collecting an independent impact exposure dataset in American football. This video assessment protocol can be implemented in

other contact sports. We have also developed a new head impact exposure metric for American football based on the number of head impacts occurring per player-play. We have found players sustain significantly more impacts per player-play in practices (0.26) than in games (0.40) ($p<0.05$). This method can provide additional independent exposure information to verify exposure data gathered using wearable sensors that are not fully validated. The verified exposure information can be used to better manage players so that they are not over-exposed to potentially dangerous head impact events.

Research Involving Human Participants

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This study was approved by the Stanford University Internal Review Board IRB #34943. Informed consent was obtained from all individual participants included in the study.

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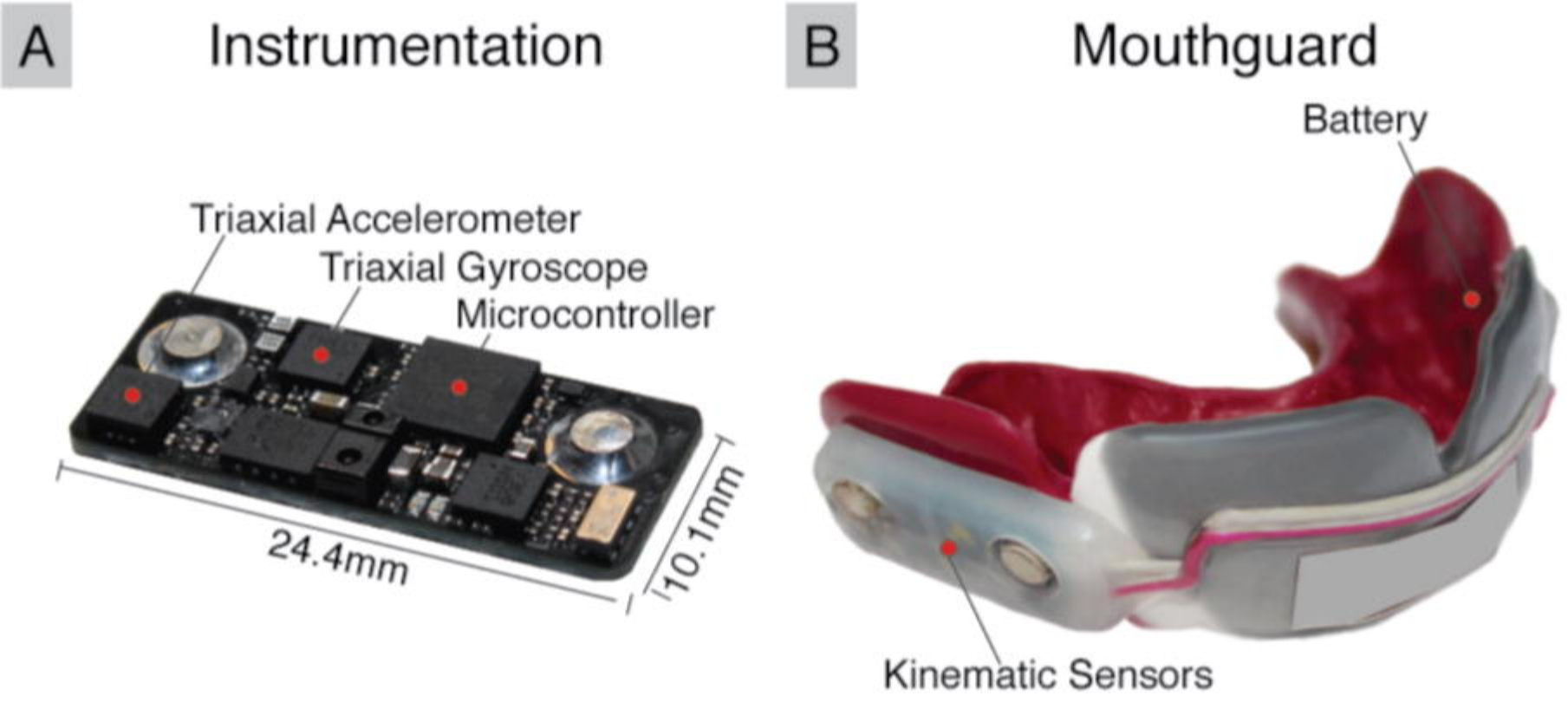
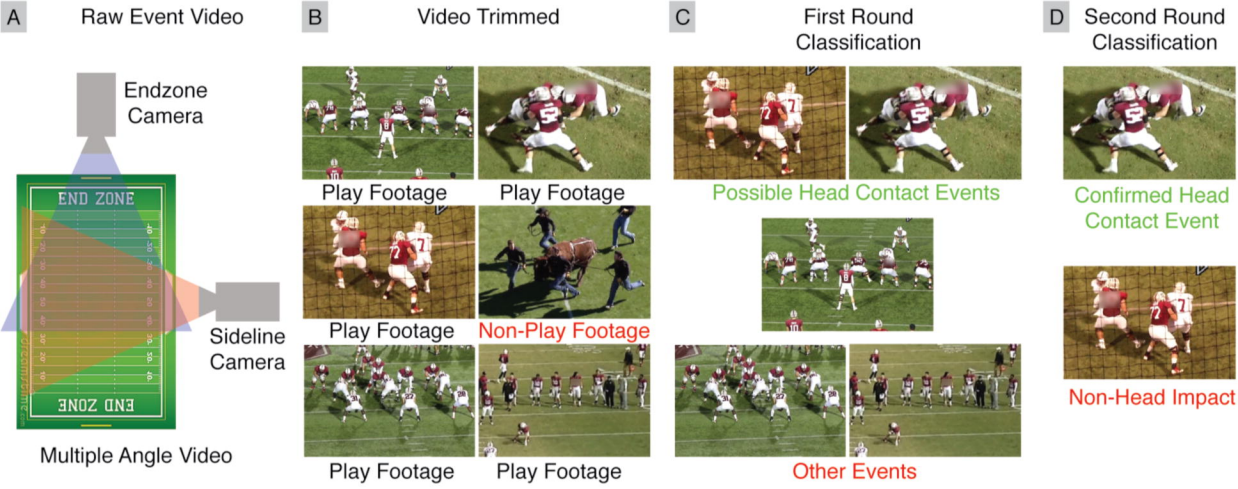
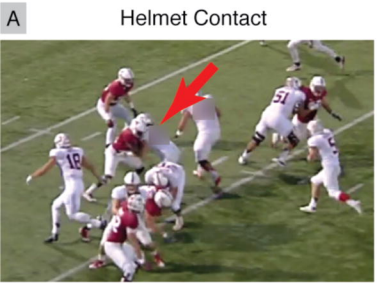
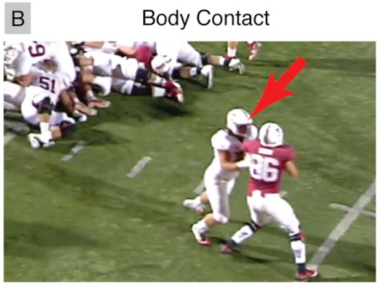
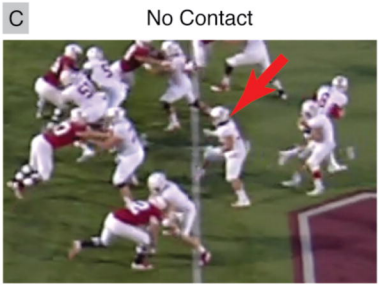
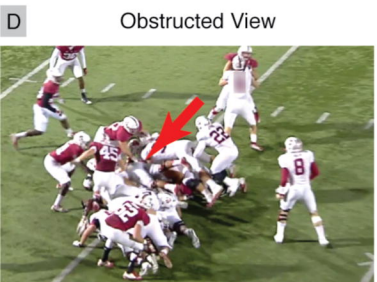

A
Instrumentation
Triaxial Accelerometer
Triaxial Gyroscope
Microcontroller
24.4mm
10.1mm
B
Mouthguard
Battery
Kinematic Sensors


A
Raw Event Video
Endzone Camera
END ZONE
Sideline Camera
END ZONE
Multiple Angle Video
B
Video Trimmed
Play Footage
Play Footage
Play Footage
Non-Play Footage
Play Footage
Play Footage
C
First Round Classification
Possible Head Contact Events
Other Events
D
Second Round Classification
Confirmed Head Contact Event
Non-Head Impact


A
Helmet Contact


B
Body Contact


C
No Contact

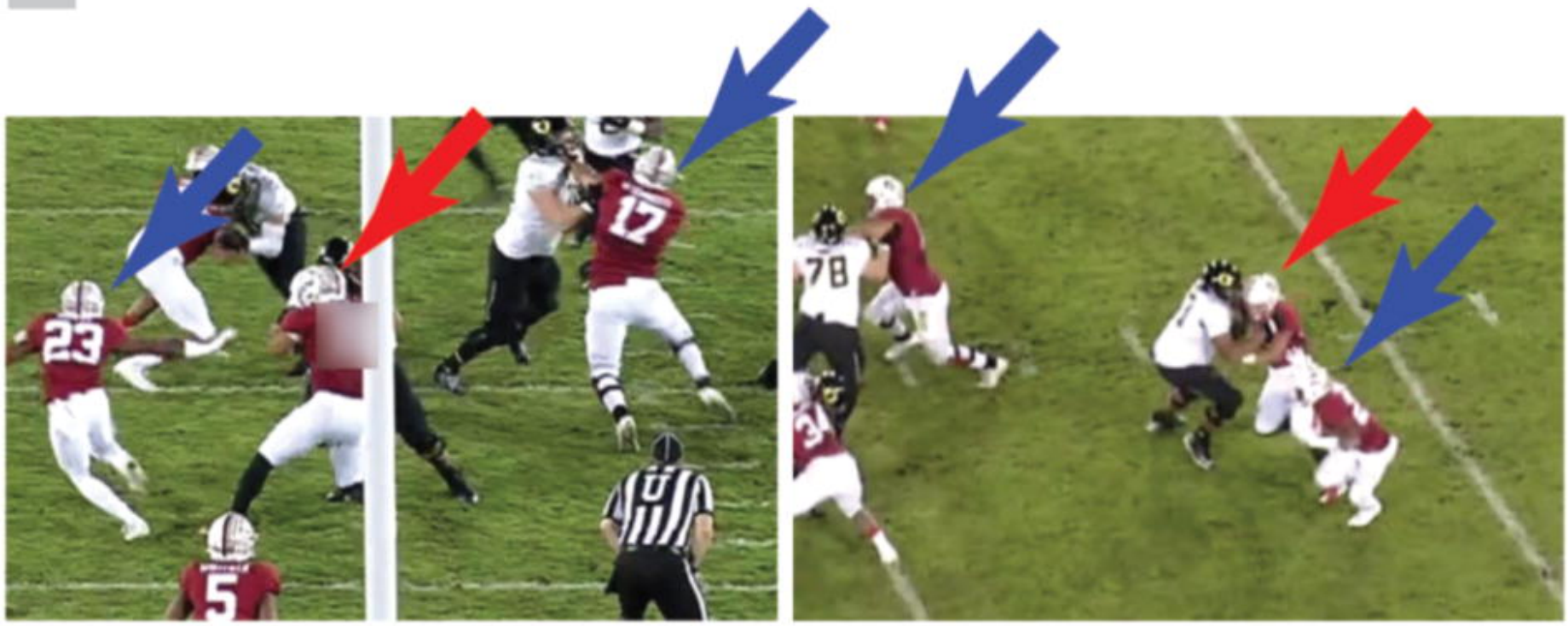

D
Obstructed View

E
Idle

F
Not in Video

A

Multi-View Confirmed Head Contact



Endzone View
Possible Contact

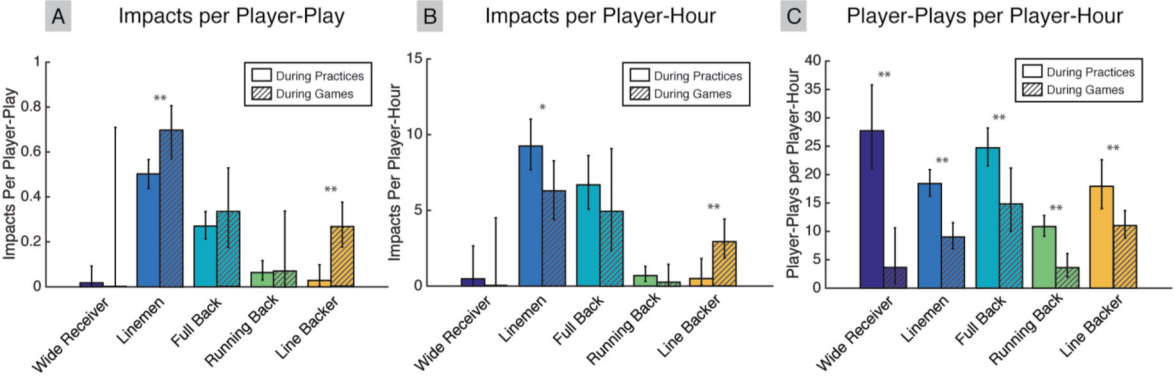
Sideline View
Confirmed Contact

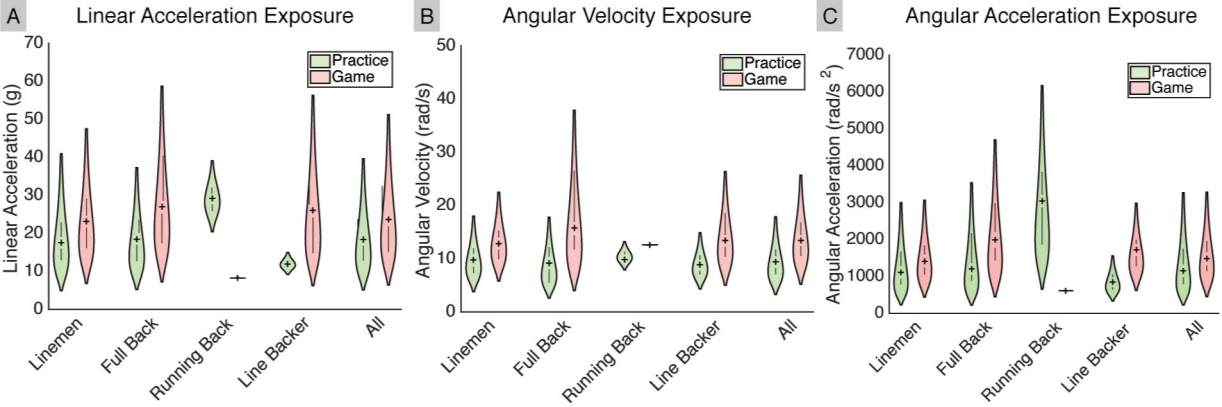
B

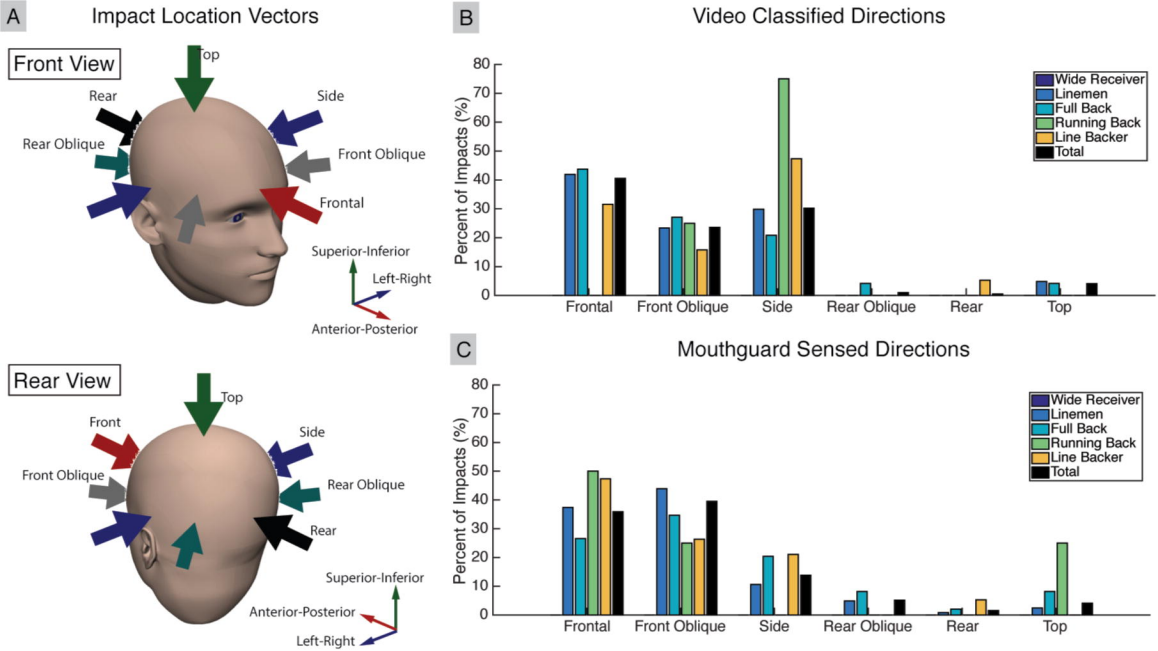
Multi-View False Positive Head Contact

Endzone View
Possible Contact

Sideline View
No Head Contact


A
Impacts per Player-Play
Impacts Per Player-Play
During Practices
During Games
Wide Receiver
Linemen
Full Back
Running Back
Line Backer
B
Impacts per Player-Hour
Impacts Per Player-Hour
C
Player-Plays per Player-Hour
Player-Plays per Player-Hour


A
Linear Acceleration Exposure
Linear Acceleration (g)
70
60
50
40
30
20
10
0
Practice
Game
Linemen
Full Back
Running Back
Line Backer
All
B
Angular Velocity Exposure
Angular Velocity (rad/s)
50
40
30
20
10
0
Practice
Game
Linemen
Full Back
Running Back
Line Backer
All
C
Angular Acceleration Exposure
Angular Acceleration (rad/s 2)
7000
6000
5000
4000
3000
2000
1000
0
Practice
Game
Linemen
Full Back
Running Back
Line Backer
All


A
Impact Location Vectors
Front View
Top
Rear
Side
Rear Oblique
Front Oblique
Frontal
Superior-Inferior
Left-Right
Anterior-Posterior
Rear View
Top
Front
Side
Front Oblique
Rear Oblique
Rear
Superior-Inferior
Anterior-Posterior
Left-Right
B
Video Classified Directions
Percent of Impacts (%)
0
10
20
30
40
50
60
70
80
Frontal
Front Oblique
Side
Rear Oblique
Rear
Top
Wide Receiver
Linemen
Full Back
Running Back
Line Backer
Total
C
Mouthguard Sensed Directions
Percent of Impacts (%)
0
10
20
30
40
50
60
70
80
Frontal
Front Oblique
Side
Rear Oblique
Rear
Top
Wide Receiver
Linemen
Full Back
Running Back
Line Backer
Total