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Development and validation of a sensor-based algorithm for detecting visual exploratory actions

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Abstract—Wearable sensors are becoming widely used in the sport sciences to assess the performance of athletes. Advances in Microelectromechanical systems (MEMS) technology, in particular inertial measurement units (IMUs), provide researchers and practitioners with a portable means of capturing performance in representative task scenarios. Of recent interest to sport scientists in team-sports is how athletes perceive their surroundings and how visual (and other) information is used to select appropriate actions during a match. Collectively, the movements athletes make to gather information from their environments is referred to as *exploratory action*. An important aspect of this behavior is typically measured by notating (counting) the number of head turns from a third-person video perspective. Notational analysis is a labor-intensive task and prone to human error, especially when activity takes place over long durations. IMUs are well suited to resolve these issues; they are highly accurate, very efficient, and have an adequate output data rate. Currently no gold standard method exists to automatically detect head turn events from IMUs. In the current study, a novel algorithm is presented that utilizes data captured from a head-mounted IMU to count the number of head turns performed by an athlete during a controlled experimental task. Results demonstrate the presented algorithm is an appropriate and efficient method for assessing the number of head turns as a measure of exploratory actions.

Index Terms—inertial sensors, magnetic sensors, head movement, exploration

I. INTRODUCTION

Understanding how athletes can prospectively guide their actions and make successful decisions in dynamic, fast-paced, and ever-changing environments is a key research problem faced by sport scientists. In team-sports, athletes must visually perceive their surroundings and use the visual information gained to prospectively guide their actions and select an appropriate action during a match [1]. The movements that athletes make to gather information from their environment includes the movement of the eyes, head, and body which collectively, is referred to as exploratory action [2-4].

Recent evidence examining visual exploratory action in football has demonstrated that players explored significantly more often when they were not in possession of the ball [5] and they performed successful actions more often when they explored their surroundings more frequently prior to receiving the ball [6]. Despite this evidence suggesting the importance of exploratory actions to performance in team-sport, in particular prior to gaining ball possession, a limited body of research on exploration exists. This is likely because currently no gold standard for measuring exploratory head movements exists. That is, typically, exploratory actions of athletes are measured by manually counting the number of head turns from a third-person video perspective [7]. This type of notational analysis is labor intensive and prone to human error, especially when activity takes place over long durations (e.g., a sporting event) [6]. For instance, in papers reporting exploration inferred from notational analysis, between rater agreement of 72% has been judged as acceptable [6]. For this reason, researchers have sought more efficient methods to capture exploratory actions in real-world settings [3].

Recent improvements in micro-electromechanical systems (MEMS) technology have paved the way for new analyses methods utilizing wearable sensors. One such technology advancement that has been used for more detailed and accurate analysis is inertial measurement units (IMUs). IMUs are becoming more widely used in sport science to assess the performance of athletes and as technology continues to advance the ability to track athletes in their natural environments has become possible [8, 9]. IMUs provide researchers, coaches, and athletes with a portable, efficient, and cost-effective means of capturing performance in representative task scenarios [10].

One of the advantages of IMUs, compared to utilizing notational analysis for measuring exploratory actions, is the rate at which data can be captured. Typically, video of match scenarios or training drills is captured at 50Hz (although more modern cameras are capable of 120Hz), whereas IMUs are capable of much higher capture rates (e.g., 250Hz and higher). Higher data capture rates are very important for

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more rapid movements, such as players exploring their surroundings during matches. In addition, notational analysis using video requires a level of interpretation by the individual coding. This human interpretation introduces subjectivity, of which IMUs would not be prone to.

This letter reports a quantitative assessment of exploratory actions using micro electromechanical (MEMS) inertial-magnetic sensors. In this letter, we demonstrate how head-mounted, low-cost inertial measurement units, in conjunction with the described algorithm can be used to accurately and efficiently detect head movements as a measure of exploratory action. We present a series of studies that sought to 1. validate an algorithm in a controlled (laboratory) setting, and thereby establish it as a novel method for head movement detection, and 2. compare the accuracy and reliability of current standard methodology of manual counts using video footage in a non-controlled (field) setting against the presented algorithm.

II. VALIDATION STUDY

To establish IMU head movement measurement for exploratory action measurement, the aim of this study was to confirm the accuracy of the proposed algorithm in a highly controlled laboratory scenario.

A. Procedure

A single participant was positioned in the center of five predefined positions that were labeled 0 to 4 accordingly (see Figure 1).

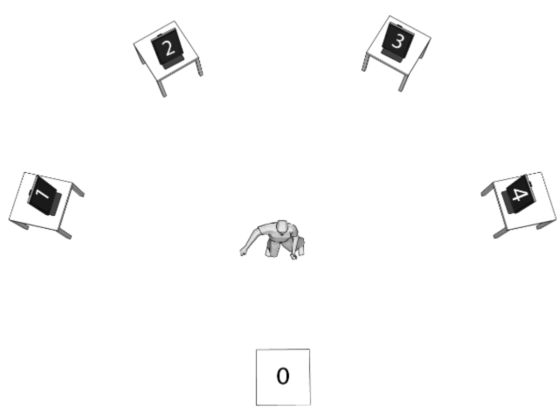

Fig. 1. Depiction of the lab layout for this study

The participant wore a head-mounted IMU that was inserted into a tight elastic pouch sewn to a soft sport headband, positioned on the occipital protuberance and started facing the position labelled 0, away from the four target positions. The participant was instructed to follow a predetermined sequence whereby they were required to turn and orient their head to face the target positions. For example, the sequence 0-1-0 required the participant to start from their initial position, turn to position one and then return to the original position. The participant was provided with the sequence prior to each trial, and could complete the sequence in their own time. No specific instructions regarding how to perform the task (e.g., speed) were provided. Only trials where the correct sequence was completed were included for analysis.

The participant completed two blocks of 12 trials (for a total of 24 trials) in a randomized order. Data was captured from a head-mounted IMU recording at 250Hz while simultaneously being video recorded.

The number of head turns was manually counted using the video recording (video count). Finally, the IMU sensor data was processed using the algorithm detailed below to provide the number of head turns detected by the sensor (sensor count).

B. Inertial Sensor Technology

A previously validated 16-bit IMU sensor (SABELSense, Griffith University, Nathan, Australia) [11-13] logged data locally to a micro SD card. The sensor incorporates a ±7 Gauss 3DOF magnetometer, a ±2000°/s 3DOF gyroscope, and a ±16 g 3DOF accelerometer and was set to capture at 250Hz.The sensor unit included an LED for video synchronization, SD card for storage, and was calibrated prior to data collection [14].

C. Algorithm Implementation

The data from the inertial sensor was downloaded to a PC for post-processing. A custom software program was created utilizing MATLAB (MathWorks, Massachusetts, USA) to determine the number of times the participant wearing the head-mounted sensor turned their head.

The software utilized a 9DOF orientation filter [15] to transform the sensor position into a global reference system, with respect to the earth's magnetic frame of reference. This orientation filter provides sensor orientation in quaternion representation which is then transformed into Euler angles. The sensor was attached so that the rotation axis of interest occurred around the yaw axis. The yaw-axis angles (in radians) were corrected for using the inbuilt MATLAB function, 'unwrap' (Mathworks, Massachusetts, USA). This unwrapped data was passed through a 10-frame moving gradient function [16], which produced the resultant slope of the yaw velocity (see Figure 2).

Following this, the intersection points of the yaw velocity were detected where they intersected a threshold of ±0.5 degrees/frame (which equates to 125 degrees/sec). This was a marker for the onset of a head turn.

Finally, a threshold detection algorithm was used to find sudden changes in sensor orientation that occurred between these intersection points. If multiple peaks were detected within 25 frames of each other, only the larger peak was included. We used 25 frames as this equates to 100ms, which has been used in eye tracking research as the minimum duration required for a fixation (the period during which an eye is fixated on a particular point of interest) [17]. The purpose of this peak detection method was to identify moments within a head turn that the orientation of the sensor began to slow down but didn't return to the threshold set above. These peaks link to instances where an individual would appear to briefly pause before continuing their head movement. As such these instances were also counted as head movements. In Figure 2 we depict an example where this occurs, which results in a total of five head movements being detected.

D. Results

Based on the search sequences provided to the participant, we expected a total of 72 head turns to be detected. The MATLAB software successfully detected all 72 head turns performed by the participant (36 in each of the two trial blocks). This was also confirmed by comparing the number of head turns detected by the software with the number of turns visually detected in the video counts.

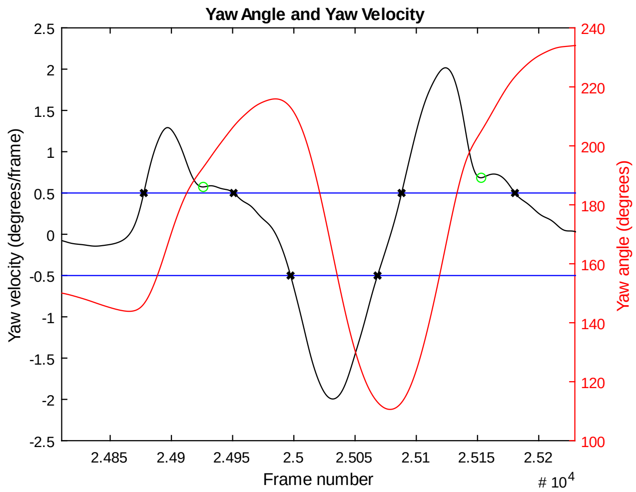

Fig. 2. Example of the resultant slope of the yaw velocity with intersect points (black stars) and peak locations (green circles) indicated. On the secondary axis is the yaw angle of the head-mounted sensor. This example depicts a total of 5 head movements.

E. Discussion

The results of the validation study demonstrated that the proposed sensor-based algorithm is capable of accurately detecting head turn events in a lab-based controlled environment. This was an important step of validation for the algorithm, as controlling the number of head turns (by providing a specific sequence) allowed a direct comparison of its accuracy. Not only did the sensor algorithm successfully detect the correct number of head turns in each of the 24 trials, it was able to do so in a matter of seconds without any subjective interpretation.

III. RELIABILITY STUDY

The aim of this study was to expand on the results reported in the validation study, and compare the accuracy of the proposed algorithm with head count measurement achieved through notational means, in a non-controlled field scenario. Additionally, the aim of this study was to demonstrate that video-based notational analysis methods are prone to human errors that are not present in sensor-based methods.

A. Procedure

A 2-minute video clip was prepared that depicted a football player in a training environment visually exploring their surroundings using a standard video camera (Sony RX100M4, Tokyo, Japan) captured at 50Hz positioned on a stationary tripod. The player was asked to make head turns in his own time, of varying speeds, to imagined opponents on both his left and right. No specific instructions regarding exploratory head movement was provided to the player e.g., when or where to look. Simultaneously, data was recorded from the same head-mounted IMU as described in Study 1.

Ten participants (7 male and 3 female) between the ages of 20 and 42 volunteered to participate. Participants were asked to count the number of times the player in the clip performed a clearly distinct change in head orientation. Participants completed this task using a customized MATLAB application that allowed participants to watch the video and record when a head turn occurred by pressing the 'H' key on a computer keyboard. Participants were able to watch the video in slow motion, rewind, or pause the video as they required.

B. Data Analysis

The data from the head-mounted IMU was passed through the same algorithm that was described in Study 1.

C. Results

The results of the analysis are reported in Table 1 below. The number of head turns that were detected by the IMU algorithm was 188. Analysis revealed that the number of head turns detected by the IMU algorithm was significantly more than by participants using video-based manual counting ($M = 170.40$, $SD = 6.19$, $t(9) = -9.00$, $p < 0.001$). Furthermore, the IMU algorithm always detected more head turns than the video-based manual head count method.

Table 1: Number of head turns manually counted by participants

Participant	**Count**	**Difference**
1	174	-14
2	161	-27
3	173	-15
4	162	-26
5	169	-19
6	166	-22
7	171	-17
8	176	-12
9	171	-17
10	181	-7
Mean	170.4 ± 6.19	-17.6 ± 6.19

D. Discussion

The results of the validation study demonstrated that human error is present in the notational analysis method. Even in our very short two-minute video, participants, on average, detected 17 (slightly over 10%) less head turns (or 8.5 head turns per minute) when compared to the algorithm method. If this discrepancy is extrapolated over the duration of an entire football match (90 minutes) this would equate to 765 head turn events not being detected, which presents an issue for researchers adopting this method. The difference in the number of head turns detected is likely two-fold. Firstly, the IMU has a much higher sampling frequency compared to standard video cameras (250Hz vs. 50Hz). This much higher sample rate provides a greater sensitivity to very small changes in acceleration and consequently change in orientation that is extremely difficult to detect using video-based methods. Secondly, the IMU algorithm is not subject to judgement errors that are present in the video notational analysis method. In the video method, individuals are often required to use their judgement regarding whether a head turn has occurred or not, which subsequently explains the variation in the number of head turns detected by participants in this experiment.

IV. GENERAL DISCUSSION

The aim of this study was to establish IMU head movement measurement as a novel method for exploratory action measurement. To this end, an algorithm was presented and validated in a controlled lab-based scenario. The major difficulty of validating such an algorithm is that the standard practice is to utilize video-based manual counting techniques. As this method has inherent accuracy issues, demonstrating agreeance between the two methods is challenging. As such, the task described in our validation study allowed for controlling the number of head turns we expected to detect. For example, when the participant was instructed to perform the sequence 0-1-0, we would expect two head turns, one to view position one and another to return to the starting position. This control task was able to remove ambiguity regarding if a head turn had occurred, and thereby providing a match between self-report, video counted and sensor detected head turns.

In the reliability study we highlighted the inherent issues of utilizing video-based detection methods through the within-subject variance of counts derived from notational analysis. In addition to the high variability in counts, the time required to detect these head turns using video was much greater than the time needed by the presented algorithm.

Before this novel algorithm is able to be called a gold standard for measurement, future work is required. For instance, further validation of the algorithm in real-world field-based scenarios is required to confirm whether the current thresholds for detection are appropriate when the speed and size of head movements are match specific. In addition, this algorithm has been tested within controlled and semi-controlled environments where sport-related movements (e.g., a header in football) were not present. Future work should further improve the algorithm to ensure these events are not detected has exploratory.

However, the presented novel algorithm for head movement measurement opens up important new avenues for exploration research. Since the algorithm-based head counts measured are derived from time-locked continuous orientation data collected by the IMU, they can be used to develop other orientation, angle, or temporal variables, such as head movement frequency, and head movement excursion. For instances, synchronizing IMU data with global/local positioning system data may provide further information about the exploratory actions used by athletes in team-sports.

V. CONCLUSION

In this paper, we presented a novel sensor-based algorithm that can quickly and accurately detect head turns from a single head-mounted IMU. We demonstrated that the algorithm was capable of efficiently detecting the number of head turns completed during a controlled task. Given the ease of setting up a single IMU and the automated processing utilizing MATLAB, we demonstrate this as an appropriate and highly efficient method for assessing the number of head turns and thus a measure of exploratory actions.

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