Assessment of a Novel Algorithm to Determine Change-of-Direction Angles While Running Using Inertial Sensors

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[1]*School of Medical and Health Sciences, Edith Cowan University, Perth, Western Australia, Australia;* [2]*Fremantle Dockers Football Club, Perth, Western Australia, Australia;* [3]*School of Engineering, Edith Cowan University, Perth, Western Australia, Australia;* [4]*Center for Exercise and Sports Science Research, Edith Cowan University, Perth, Western Australia, Australia;* [5]*Exercise Medicine Research Institute, Edith Cowan University, Perth, Western Australia, Australia; and* [6]*Institute for Health Research, University of Notre Dame Australia, Fremantle, Western Australia, Australia*

Abstract

Balloch, AS, Meghji, M, Newton, RU, Hart, NH, Weber, JA, Ahmad, I, and Habibi, D. Assessment of a novel algorithm to determine change-of-direction angles while running using inertial sensors. *J Strength Cond Res* XX(X): 000–000, 2019—The ability to detect and quantify change-of-direction (COD) movement may offer a unique approach to load-monitoring practice. Validity and reliability of a novel algorithm to calculate COD angles for predetermined COD movements ranging from 45 to 180° in left and right directions was assessed. Five recreationally active men (age: 29.0 ± 0.5 years; height: 181.0 ± 5.6 cm; and body mass: 79.4 ± 5.3 kg) ran 5 consecutive predetermined COD trials each, at 4 different angles (45, 90, 135, and 180°), in each direction. Participants were fitted with a commercially available microtechnology unit where inertial sensor data were extracted and processed using a novel algorithm designed to calculate precise COD angles for direct comparison with a high-speed video (remotely piloted, position-locked aircraft) criterion measure. Validity was assessed using Bland-Altman 95% limits of agreement and mean bias. Reliability was assessed using typical error (expressed as a coefficient of variation [CV]). Concurrent validity was present for most angles. Left: (45° = 43.8 ± 2.0°; 90° = 88.1 ± 2.0°; 135° = 136.3 ± 2.1°; and 180° = 181.8 ± 2.5°) and Right: (45° = 46.3 ± 1.6°; 90° = 91.9 ± 2.2°; 135° = 133.4 ± 2.0°; 180° = 179.2 ± 5.9°). All angles displayed excellent reliability (CV $<$ 5%) while greater mean bias (3.6 ± 5.1°, $p < 0.001$), weaker limits of agreement, and reduced precision were evident for 180° trials when compared with all other angles. High-level accuracy and reliability when detecting COD angles further advocates the use of inertial sensors to quantify sports-specific movement patterns.

Key Words validity, accuracy, reliability, microtechnology, signal processing, accelerometry

Introduction

Change-of-direction (COD) movements (preplanned and reactive) are characterized by whole-body changes of velocity requiring high magnitudes of vertical, mediolateral, and anterior-posterior impulses to move quickly and efficiently (6,34). Each COD event involves a braking and propulsive phase, which highlights the importance of eccentric-concentric muscle actions for both force production and muscular endurance as the number of directional changes increases (6). As the occurrence of these movements increases, high levels of muscle damage and neuromuscular fatigue become prevalent (6,33). The accumulation of both acute and chronic fatigue may alter movement strategy and compromise mechanical efficiency of movement during subsequent efforts or exercise bouts (32). Without adequate recovery, a reduction in movement efficiency may alter mechanical loading on lower-body joints and inherently increase the risk of injury (13,30). If such changes in mechanical loading can be identified, quantified, examined, and subsequently integrated into load-management practice through a wearable technology, effective strategies may be developed to enhance performance and reduce injury risk through individually tailored, sport-specific conditioning interventions.

Global positioning system (GPS) technology is principally used in team sports to monitor athletes during on-field training and competition by transmitting instantaneous triangular positioning information that is used to formulate a multitude of distance-, time-, and speed-derived metrics (11,36). This technology is widely used within elite sport as a performance analysis tool (9,11), and although it has the capability to accurately calculate accumulated distance

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when movement is largely linear (8,27), it is inherently prone to error during short duration, high-speed movements (10,26) and even more so when these movements incorporate nonlinear characteristics (e.g., COD movement) (14,25). In addition, this technology appears to be approaching its limits with regard to more advanced movement tracking whereby an optimal sampling frequency (10 Hz) has been proposed (26), suggesting alternate technologies may be required to accurately identify and quantify more complex, sports-specific movement patterns.

Inertial sensors (accelerometers, gyroscopes, and magnetometers) within wearable technology have previously been used to detect physical activity and sleep patterns in both clinical and general populations (9,28), and to more precisely differentiate between a range of activities from sitting and standing to walking, running, and jumping by assessing vector quantities of acceleration in 3 dimensions (anterior-posterior, mediolateral, and vertical) with high levels of validity (both construct and concurrent) and reliability (3,9). Commercially available GPS devices implemented in elite sport currently house these inertial sensors colocated within the same unit casing as the GPS engine, which have the capability to accurately identify, record, and quantify more sport-specific movements (4), yet tend to be underused in the professional environment and within the proprietary software. These inertial sensors sample at a much higher frequency than GPS engines (most commonly 100 Hz) and can therefore detect subtle changes in movement within the 3-dimensional environment that GPS technology is presently incapable of (9). In addition, inertial sensors work independently of satellite reliant GPS technology and can therefore be implemented indoors (9), superseding a fundamental limitation of GPS engines when used in isolation.

In a team-sport environment, inertial sensor technology has been effectively used to quantify a range of different movements from jumps to collisions, impacts, and tackles (5,16–18,38). Furthermore, signals from inertial sensors coupled with various pattern recognition techniques have successfully been used to create algorithms that automatically detect and categorize collisions and tackles in heavy contact sports such as Australian rules football and rugby league (16,17), and a range of different activities including rotational magnitude of aerial acrobatics in snowboarding (20), kick count in swimming (15), and more recently, an entire fast-bowling event in cricket (31).

Although these inertial sensors have previously been assessed for their ability to detect and analyze a number of different multiplanar "sports-specific" movements (15,16,20,31,38), these studies are infrequent, and to the best of our knowledge, these sensor signals are yet to be used to accurately distinguish COD movement from other variables from within a commercially available microtechnology unit.

Given the neuromuscular implications associated with repeated COD movements, highly prevalent in team sports (12), and the subsequent effect resulting fatigue may have on the movement efficiency of an athlete, there is clear rationale for nonlinear movement patterns to be further assessed and included in both acute and chronic load-monitoring practice. Therefore, the current study is a description of the use of inertial sensor technology (accelerometers, gyroscopes, and magnetometers) to develop an algorithm that is able to automatically detect and record COD movements ranging from 45 to 180° (both left and right directions) and concomitantly assesses the validity and reliability of the calculated COD angle.

Methods

Experimental Approach to the Problem

This concurrent validity study was designed to investigate the accuracy of a novel algorithm to automatically detect

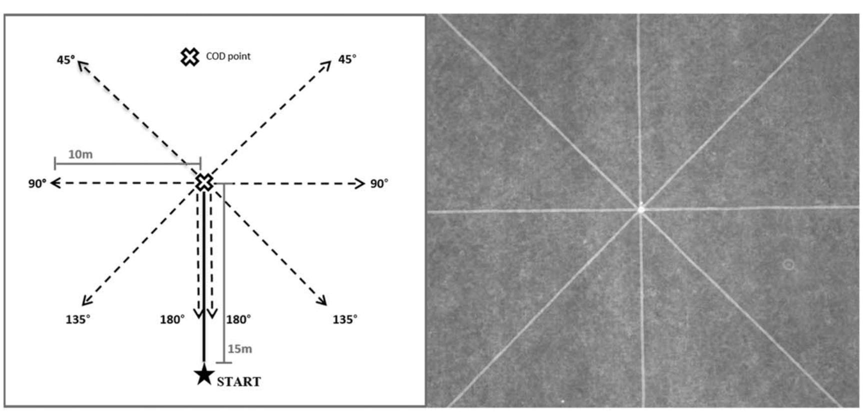

Figure 1. Aerial view and schematic representation of the premarked COD grid displaying all COD angles that participants were required to run. COD = change of direction.

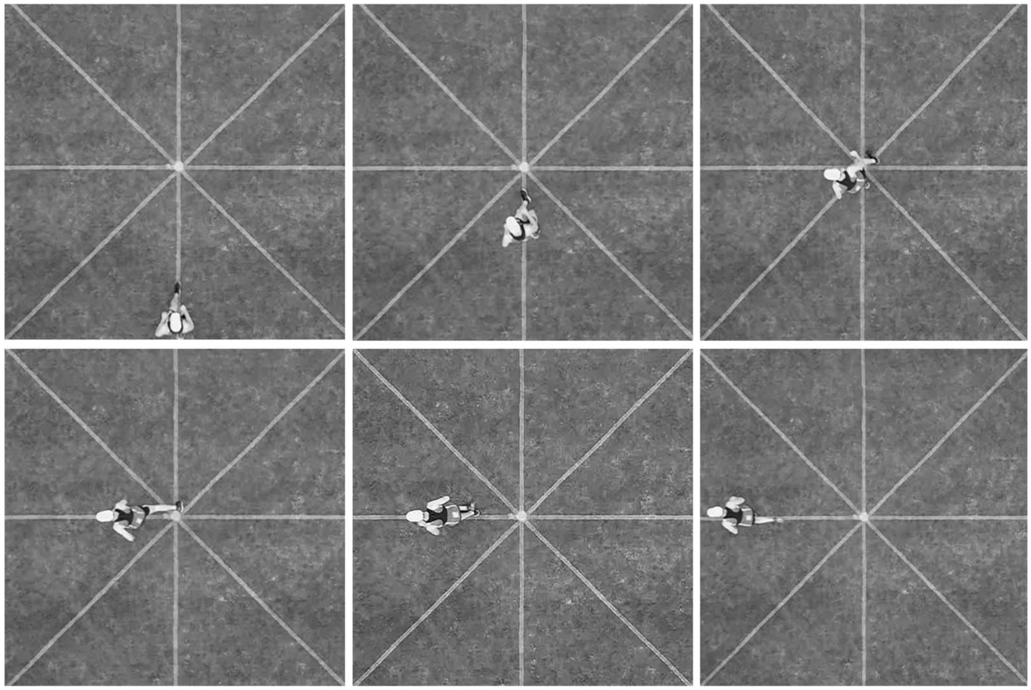

Figure 2. A sample of the high-speed video footage recorded by the remotely piloted aircraft displaying the requirements of each participant to run directly on a clearly marked straight line before changing direction (90° to the left in this example) at a marked center point, then continuing on another straight line in accordance with the intended direction and angle.

and quantify COD angle against a high-speed video criterion measure. Participants were required to run a series of single, predetermined COD trials consisting of 4 different angular changes (45, 90, 135, and 180°) in each direction (left and right). Each participant was required to run 5 COD trials at each angle in each direction (i.e., 40 trials per participant) wearing a commercially available and commonly used microtechnology unit (Optimeye, S5; Catapult Innovations, Melbourne, Australia) on an outdoor football field. A remotely piloted aircraft (drone; Mavic Pro; DJI, Shenzhen, China) was position-locked above the marked COD center point to record all trials for comparison between measurement devices and for visual confirmation of correct running lines (Figure 1).

Subjects

Five recreationally active men (mean ± *SD*; age, 29.0 ± 0.5 years; height, 181.0 ± 5.6 cm; and body mass, 79.4 ± 5.3 kg) volunteered to participate in this study. All participants were free from injury and medical conditions that would contraindicate participation in physical activity. The study was ethically approved by the Edith Cowan University's Institutional Review Board, and subjects were informed of the benefits and risks of the investigation before signing an institutionally approved informed consent document to participate in the study.

Procedures

Testing Protocol. Before commencement of testing, participants were given clear instructions to run directly on a visibly marked straight line on the ground and change direction at a marked center point before continuing to follow a second marked straight line in accordance with the intended COD and angle (Figure 2). A dynamic warm-up was undertaken before each participant completed one warm-up COD trial at each angle (45, 90, 135, and 180°) in each direction (left and right) for familiarization purposes. Participants were then required to complete 5 individual COD trials consecutively at each angle in each direction in a randomized and counterbalanced fashion (to ensure any fatigue would not have an adverse or more influential effect on a given angle or direction relative to another); therefore, all participants completed five 45° COD trials to the left before moving on to the next angle and direction. Participants were instructed to run at a moderate pace and change direction by planting the outside foot to the opposite direction in a "side-cutting" motion but were encouraged to keep each trial "as natural as possible" (Figure 2). Participants were provided with adequate rest of at least 60 seconds between COD trials and ensured compliance of 5 consecutive trials in each direction, confirmed with visual inspection using drone-footage postcollection. Each participant completed 40 COD trials, producing a total of 200 trials across the testing session.

Microtechnology. Each participant was fitted with a commercially available microtechnology unit (Optimeye, S5; Catapult Innovations) (Figure 3A) posteriorly trunk-mounted (at the level of the upper thoracic vertebrae (T1–T5) between the medial borders of the scapulae) in a manufacturer-supplied, fitted vest (Figure 3B). This microtechnology unit houses a 10-Hz Global Navigation Satellite System antenna along with a triaxial accelerometer, triaxial gyroscope, and triaxial magnetometer, all sampling at 100 Hz. Each unit was calibrated in accordance with the manufacturer's guidelines before the commencement of the testing session. Raw data were extracted from the microtechnology unit using the manufacturer-designed, proprietary software (Catapult Sprint 5.1; Catapult Innovations) for subsequent exportation and analysis.

Algorithm Creation. Data analysis and algorithm creation were performed using MATLAB (MathWorks, Natick, MA, USA), whereby a multistage algorithm was developed incorporating triaxial inertial sensor inputs that align with the athlete's body in such a way that the x, y, and z rotations correspond to the *roll* (mediolateral), *pitch* (anterior-posterior), and *yaw* (superior-inferior) axes of the inertial sensors (Figure 4). This algorithm provides a series of signal processing computation and decision techniques to first detect that a COD movement has occurred; second detect the direction of the COD movement; and third report the precise COD angle.

Figure 3. A) Catapult Optimeye S5 microtechnology unit (52 × 96 × 12 mm), housing a 10-Hz global navigation satellite system antenna, along with a triaxial accelerometer, gyroscope, and magnetometer, all sampling at 100 Hz; and (B) commercially manufactured, trunk-mounted, fitted vest displaying the placement of the microtechnology unit.

Heading Angle Calculation. Initial stages of the algorithm required input from each of the inertial sensors (accelerometer, gyroscope, and magnetometer) to optimize accuracy when computing the "yaw" (also known as the heading or azimuth) angle. First, the gyroscope output was time-integrated by mapping the rate of change of angular velocity (w) (i.e., angular velocity/time) from an initially known orientation.

From the relationship: $w = \frac{d\theta}{dt}$; $d\theta = w \cdot dt$.

The overall angle change (yaw) was found by summating this quantity over many samples and then using a rotation matrix to determine the Euler yaw angle (rotation around the z-axis).

Therefore, $\theta = \int_{t+T}^{t} w \cdot dt$ or $\theta = \sum_{t+T}^{t} w \times \Delta t$.

Second, the magnetometer output is able to accurately compute heading location by using the Earth's magnetic field (when parallel to the Earth's surface). However, a moving athlete will inevitably cause the magnetometer to move away from the horizontal plane (tilt) causing errors in subsequent calculations (40). Therefore, triaxial accelerometer data were used to calculate roll and pitch angles, which were subsequently integrated with the magnetometer data to correct this tilt error by mapping the magnetometer data to the horizontal plane providing an accurate heading calculation, regardless of the magnetometer's position.

Finally, a complementary filter was used to obtain the final yaw angle estimation by integrating gyroscope and magnetometer yaw angle calculations for the strongest and most accurate sensor computation.

Change-of-Direction Angle Calculation. The "yaw" angle calculation obtained (as described above) then entered a secondary stage of the algorithm (a modified Canny edge detection algorithm (7)), which principally follows a 5-step process from the input of the yaw angle, to the detection of a COD movement, determination of a direction, and calculation of a precise angle.

Initially, a customized 2D Gaussian filter was used to remove any "noise" from the yaw signal. The next step involved determining the intensity gradient of the yaw angles in both horizontal and vertical planes to provide both magnitude and direction. This

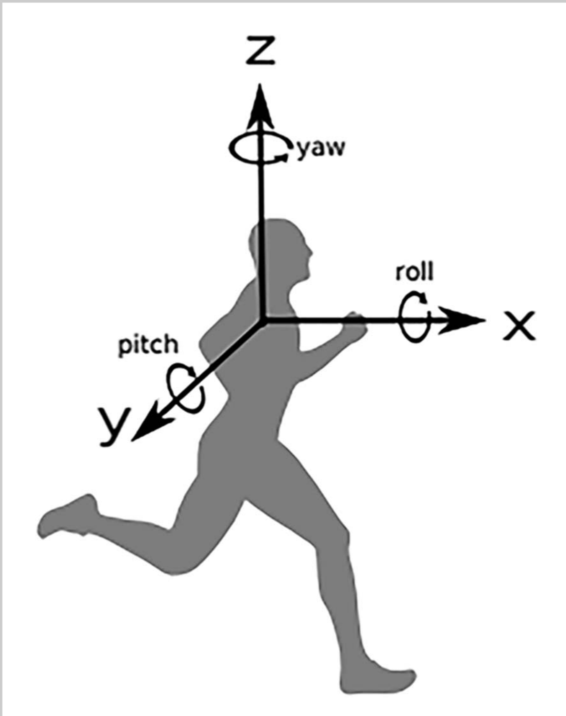

Figure 4. A visual representation of the triaxial nature of the inertial sensors housed within a trunk-mounted wearable microtechnology unit for human locomotion (yaw, pitch, and roll).

was followed by a nonmaximal suppression stage whereby a full scan of yaw angles was completed to identify the local maxima or peak (maximum change in gradient) while the rest of the samples were suppressed and set to zero. From here, hysteresis thresholding was used to identify "real" edges based on predetermined threshold values that differ with variations in the angle. These edge values were then extracted and entered into a multilevel piecewise thresholding algorithm (based on a piecewise linear relationship between the edge value and calculated angle change [yaw angle]) to calculate a precise COD angle.

High-Speed Video Analysis. A remotely piloted aircraft (drone; DJI Mavic Pro, DJI, Shenzhen, China) was positioned 15 m above the center point of the marked COD grid and locked in position, remaining completely stationary for the duration of the testing session (lasting ~30 minutes). An in-built high-definition camera (1/2.3″ CMOS 12MP 4K) recorded each COD trial at a sampling rate of 96 frames per second. Each COD trial was visually inspected after collection to ensure the drone was positioned correctly and remained completely still to ensure valid trials were recorded. Subsequent video analysis was performed using Kinovea software (Kinovea, 0.8.15, http://www.kinovea.org/) where each COD trial was analyzed to allow for a direct and quantifiable comparison between the algorithm-derived COD angle and the high-speed video-derived COD angle.

After visual inspection, a preset distance of 2 m either side of the COD center point was deemed the beginning and the end of the COD trial, ensuring participants were "yet to commence" and had "completed" the COD in each trial, respectively (Figure 5). This predefined distance was precisely measured during analysis using a software calibration tool (Kinovea, 0.8.15) from a premeasured and clearly marked point (measuring 1 m) on the COD grid. A reflective marker was fixed to the exterior of the vest where the microtechnology device was housed to allow for clear determination of the device's position during video analysis to maximize precision when calculating the COD angle. The COD angle was determined using an angle measuring tool within the software (Kinovea, 0.8.15), which intersected the location of the posteriorly trunk-mounted microtechnology device at both reference points (2 m either side of the COD center point), thus calculating the resultant angle (Figure 5).

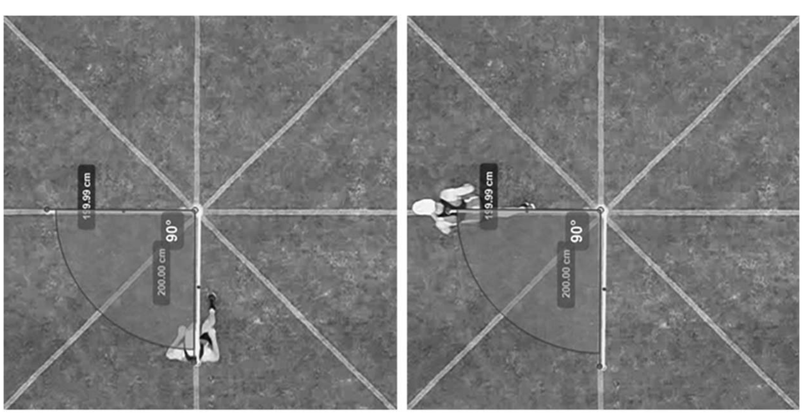

Figure 5. A sample of a single COD (90° to the left) analyzed using high-speed video to determine the precise angle that the participant changed direction, in relation to the intended marked path. COD = change of direction.

Velocity Determination. Instantaneous velocity measures were derived from the GPS engine (Optimeye S5, Catapult Innovations) and extrapolated using the identical proprietary software to that mentioned previously (Catapult Sprint 5.1, Catapult Innovations). "Pre-COD average velocity" was defined as the average velocity over 2 seconds preceding the point of COD,

Table 1. Accuracy, validity, precision, and reliability of the proposed COD algorithm in comparison with a high-speed video criterion measure for COD angle accuracy ($n = 194$).*

COD angle		High-speed video (mean ± *SD*)	Algorithm (mean ± *SD*)	Mean bias ± *SD*	% Diff	Effect size (Cohen's *d*)	95% LoA (°)	RMSEP (°)	TE ± 90% CI (°)	CV (%)	Pre-COD Avg Vel ($m \cdot s^{-1}$)	Post-COD Avg Vel ($m \cdot s^{-1}$)	Total COD Avg Vel ($m \cdot s^{-1}$)
Left	45	46.1 ± 1.9°	43.8 ± 2.0°	−2.3 ± 2.7°†	−5.1	−0.81	−7.67, 3.01	3.55	1.9 (1.5–2.6)	4.2	3.81 ± 0.16	3.81 ± 0.11	3.79 ± 0.11
	90	91.1 ± 1.6°	88.1 ± 2.0°	−3.0 ± 2.6°†	−3.3	−1.13	−8.12, 2.16	3.93	1.6 (1.3–2.1)	1.7	3.68 ± 0.22	3.62 ± 0.16	3.52 ± 0.16
	135	136.8 ± 1.9°	136.3 ± 2.1°	−0.6 ± 2.2°	−0.4	−0.26	−4.83, 3.71	2.21	1.8 (1.4–2.4)	1.3	3.67 ± 0.21	3.55 ± 0.15	3.44 ± 0.11
	180	176.9 ± 2.9°	181.8 ± 2.5°	4.9 ± 3.7°†	2.8	1.36	−2.16, 12.00	6.05	3.0 (2.4–4.0)	1.7	3.90 ± 0.18	3.78 ± 0.32	3.62 ± 0.20
Right	45	46.6 ± 1.5°	46.3 ± 1.6°	−0.3 ± 2.3°	−0.7	−0.14	−4.80, 4.18	2.27	1.5 (1.2–2.0)	3.3	4.00 ± 0.24	3.96 ± 0.21	3.95 ± 0.19
	90	90.0 ± 2.3°	91.9 ± 2.2°	1.9 ± 2.5°†	2.2	0.76	−2.95, 6.85	3.12	2.2 (1.8–2.9)	2.5	3.52 ± 0.19	3.49 ± 0.13	3.39 ± 0.13
	135	133.8 ± 2.0°	133.4 ± 2.0°	−0.4 ± 3.5°	−0.3	−0.10	−7.27, 6.53	3.47	2.0 (1.6–2.7)	1.5	3.81 ± 0.20	3.71 ± 0.15	3.56 ± 0.14
	180	176.8 ± 5.7°	179.2 ± 5.9°	2.4 ± 6.1°	1.4	0.39	−9.51, 14.29	6.40	5.2 (4.2–6.9)	3.0	3.94 ± 0.24	3.68 ± 0.23	3.58 ± 0.18

*COD = change of direction; % Diff = percentage difference between algorithm- and criterion-derived COD angle; 95% LoA = 95% limits of agreement; RMSEP = root mean square error of prediction; TE ± 90% CI = typical error ±90% confidence intervals; CV = coefficient of variation; Pre-COD Avg Vel = pre change-of-direction average velocity; Post-COD Avg Vel = post change-of-direction average velocity; Total COD Avg Vel = total change-of-direction average velocity.

†Significant level of bias ($p < 0.05$) between criterion- and algorithm-derived COD angles.

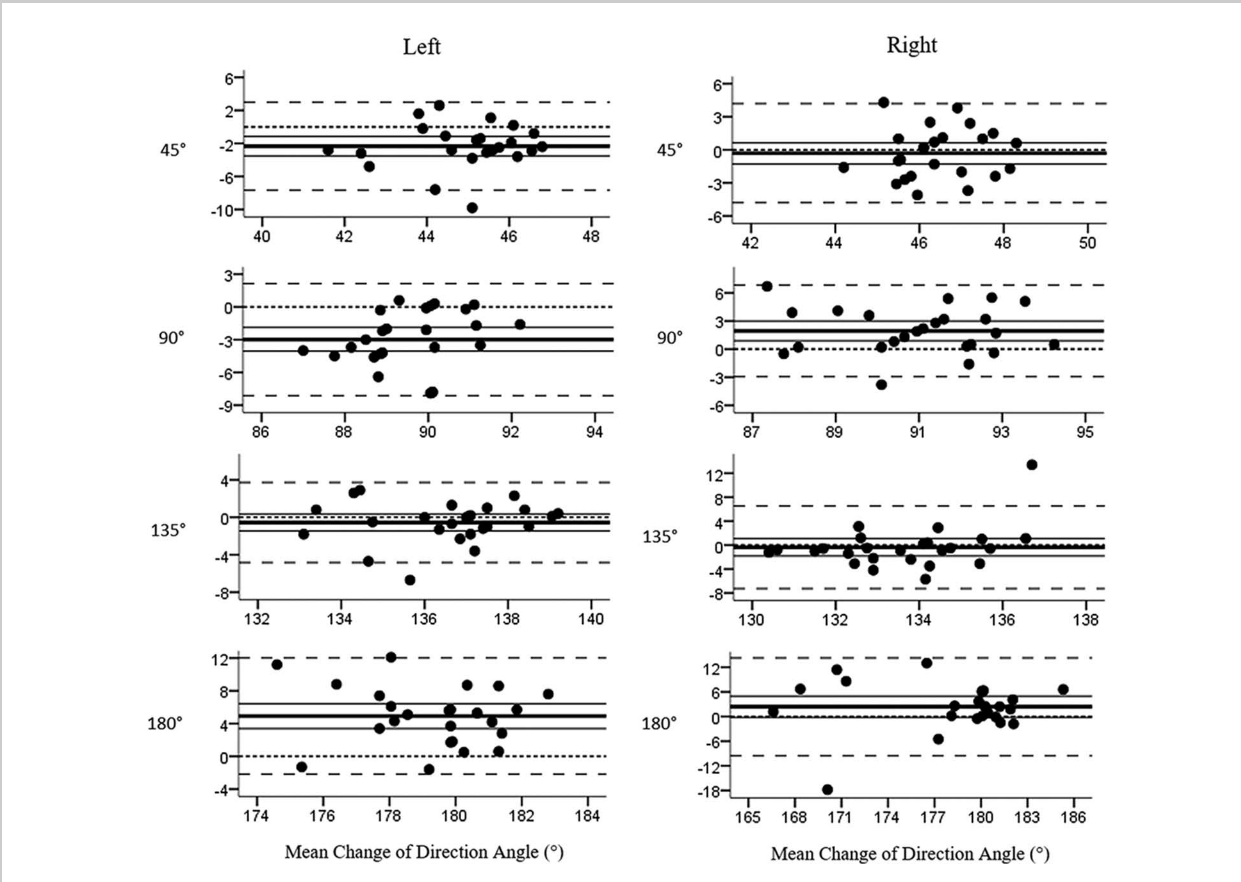

Figure 6. Bland-Altman plots showing the systematic bias in an algorithm-defined change-of-direction angle (thick black line), 95% confidence interval of the bias (thin black line), the 95% limits of agreement (dashed black line), and the line of equality (dotted black line). In each plot, the difference between algorithm-defined and high-speed video COD angle for each trial is plotted against the mean of the measurements. COD = change of direction.

"post-COD average velocity" was defined as the average velocity over 2 seconds directly following the COD point, and "total COD average velocity" was defined as the average velocity from the beginning of the "pre-COD" to the end of the "post-COD" time-stamp (including the point of COD).

Statistical Analyses

Six COD trials were removed after visual inspection, as slight movement of the remotely piloted aircraft (environmental factors) was detected during these trials. This left a total of 194 COD trials for use in the analyses. All statistical analyses were conducted using SPSS software (v24.0, SPSS Inc., NY, USA) and Microsoft Excel (Microsoft, Redmond, WA, USA) with the exception of statistical power estimation (for sample size determination) described below. Data are presented as mean $\pm$ *SD* for both high-speed video and algorithm-derived determinants of the COD angle (Table 1). Level of agreement and accuracy of the proposed algorithm was assessed by calculating the Bland-Altman 95% limits of agreement (LoA) (2) and mean bias in relation to the criterion measure (high-speed video). Effect size of the mean bias was calculated using Cohen's *d* where results were interpreted as negligible (<0.2), small (0.2–0.6), medium (0.6–1.2), large (1.2–2.0), or very large (2.0–4.0) (22). Precision or variability of bias was assessed using a root mean square error of prediction (RMSEP). Reliability was calculated using Hopkins' spreadsheet (21) and was expressed in absolute terms as typical error (TE) $\pm$ 90% confidence intervals and relative terms as a coefficient of variation (CV) percentage, where a CV < 5% was considered "good"; a CV between 5 and 10% "moderate"; and a CV > 10% "poor" as has been previously interpreted when assessing the reliability of sports analysis technology (5,25).

A one-way analysis of variance (ANOVA) was conducted on the mean difference scores (or bias) between each participant to identify any potential differences in algorithm accuracy between microtechnology devices. A second one-way ANOVA was conducted to determine any differences in mean bias across each angle (45, 90, 135, and 180°), independent of direction. Post hoc comparisons were assessed using a Games-Howell test as appropriate for heteroscedastic data. A paired samples *t*-test was used to determine any differences in mean bias between left and right direction across all angles. Sample size requirements for LoA were calculated using MedCalc Statistical Software (v18.2.1, MedCalc Software bvba, Ostend, Belgium; http://www.medcalc.org; 2018) where 10° was set as the maximum allowed difference between methods across all trials, yielding a required sample of 171 trials. An alpha level of $p \leq 0.05$ was set as the level of significance for all statistical tests.

Results

Concurrent validity and accuracy of the proposed algorithm is presented in Table 1. The results from the Bland-Altman analysis are shown in Table 1 and Figure 6. Concurrent validity was present across a number of angles (45° right, 135° left and right, and 180° right); however, the proposed algorithm slightly underestimated COD angle at 45° (−2.3 ± 2.7°, Cohen's $d = -0.81$) and 90° to the left (−3.0 ± 2.6°, Cohen's $d = -1.13$), whereas slightly overestimating COD angle at 180° (4.9 ± 3.7°, Cohen's $d = 1.36$) to the left and 90° to the right (1.9 ± 2.5°, Cohen's $d = 0.76$). No significant bias was found between the proposed algorithm and criterion measure for any other angles with a mean bias range of −0.6 ± 2.2° to 2.4 ± 6.1° and negligible to small effect size differences (Cohen's $d = -0.26$ to 0.39).

All angles were measured with good reliability (TE = 1.6–5.2°; CV = 1.3–4.2%). The Levene test of homogeneity revealed unequal variances and therefore the Brown-Forsythe ANOVA result was interpreted, revealing no significant difference in mean bias between microtechnology devices ($p = 0.25$). However, the secondary Brown-Forsythe ANOVA did reveal a significant difference in mean bias between angles ($p = 0.00$) with Games-Howell post hoc comparisons showing a significantly greater mean bias for the 180° COD trials (3.6 ± 5.1°) when compared with 45° (−1.3 ± 2.7°; $p = 0.000$), 90° (−0.6 ± 3.6°; $p = 0.000$), and 135° (−0.5 ± 2.9°; $p = 0.000$) COD trials (Figure 7). Weaker limits of agreement and precision were also apparent for the 180° trials (in both directions) when compared with all other angles (Table 1). There were no significant differences found in mean bias between 45, 90, and 135° COD trials. In addition, there was no statistically significant difference in the mean bias between left (−0.3 ± 4.2°) and right (0.9 ± 4.0°) COD trials across all angles ($p \geq 0.05$).

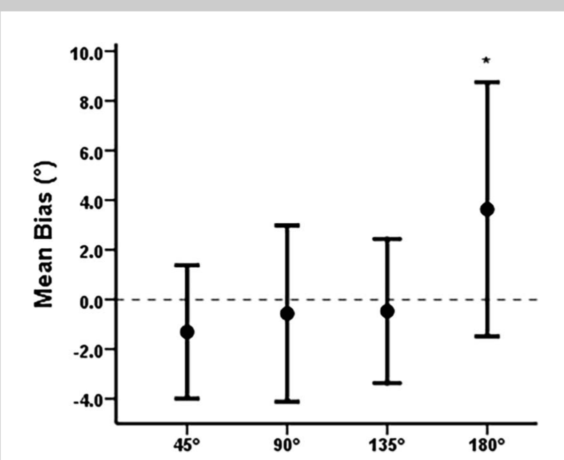

Figure 7. Mean bias ±*SD* of each COD angle independent of direction. *Significantly ($p < 0.001$) greater mean bias when compared with all other COD angles. COD = change of direction.

Discussion

The purpose of this study was to assess the validity, accuracy, and reliability of a newly developed algorithm to calculate the COD angle for predetermined COD movements ranging from 45 to 180° (both left and right) and assess the level of agreement against a criterion measure.

Our novel algorithm displayed a high level of accuracy with mean differences ranging between −3.0 ± 2.6° and 4.9 ± 3.7° (−5.1 to 2.8%) in relation to the criterion measure, and proved valid across numerous COD angles (45, 90, 135, and 180°), in both directions (left and right). Of these, the algorithm slightly underestimated the COD angle for 45 and 90° trials (left), and slightly overestimated the COD angle for 90° (right) and 180° trials (left). These results are a mild bias that may be statistically present in some cases; however, from a practically meaningful perspective, a bias of less than 5° or 6% for all COD angles could be considered insignificant when aiming to assess the mechanical load associated with COD movement for both acute and chronic load-monitoring purposes; given there is currently no alternative in detecting, recording, and reporting an exact COD angle on-field using a commercially available and commonly used microtechnology unit. However, caution is required when quantifying 180° COD movements, which evidently presented a significantly greater mean difference (bias) and showed the weakest limits of agreement (95% LoA [left: −2.16°, 12.00°, right: −9.51°, 14.29°]) and lowest precision RMSEP [left: 6.05°, right: 6.40°] when compared with the 45, 90, and 135° trials. Yet importantly, all angles displayed good reliability (TE = 1.5–5.2°; CV < 5%) between trials.

Our algorithm demonstrates a level of validity and reliability that is comparable and mostly favorable to similarly previous research whereby inertial sensor outputs have been coupled with signal processing techniques to identify more complex movement patterns. For example, categorizing rotational magnitude of aerial acrobatic maneuvers in snowboarding (20), recording kick count during freestyle swimming (15), and somewhat unsuccessfully applying a tackle detection algorithm to Australian rules football matches (18). However, these studies have typically used only one of the inertial sensors in isolation (18,23) and in some cases only analyzed a single axis of movement (15,20), whereas our algorithm uses more than one sensor and considers all axes of movement. Similar to the current study, previous research that has used the integration of multiple sensor outputs (e.g., accelerometer and gyroscope) has demonstrated a high level of success in detecting more holistic, sports-specific movement patterns such as an entire fast-bowling event in cricket (31) and quantifying the contact load of collisions in professional rugby league (16). These improved findings may be due to the ability to use the relative strengths of each inertial sensor to compensate for the weakness of another (29). The current study adds to this body of knowledge and the successful characterization of athletic movement by successfully (accurately and reliably) quantifying COD movements.

Although it has been suggested that a majority of human motion occurs at a rate of less than 20 Hz (24), it is clear that much higher sampling rates are required to accurately capture more detailed and complex movement characteristics. Within elite sport, GPS technology is used heavily by sports science and strength and conditioning staff to make informed load-management decisions in "real-time" and prospectively when periodizing and planning subsequent training sessions. However, GPS technology requires triangular signal positioning from orbiting satellites, thus requires an outdoor venue, limiting its applicability across sporting types, some outdoor venues and all indoor venues (11), and can be vulnerable to dysfunction or interference from adverse environmental conditions and other competing technologies. Furthermore, the reliability of GPS technology is considerably reduced during high-speed movements (1,10,14) and is even further compromised when measuring movement patterns that incorporate COD (25), highlighting other important limitations when using GPS to quantify player movement patterns and performance.

Global positioning system technology has improved using higher sampling rates (10 Hz) where an "acceptable" level of accuracy (CV $\leq$ 11.3%) and reliability (CV $\leq$ 6.0%) has been demonstrated when calculating instantaneous velocity during high-speed straight-line running (36), in contrast with less advanced GPS technologies (1–5 Hz sampling rate), which have proven to be less reliable when calculating instantaneous velocities during similar movement patterns (10,19,25). This logically suggests a potential linear relationship between higher sampling frequencies and greater detection sensitivity, leading to improved accuracy and reliability of GPS at higher sampling rates when measuring distance and instantaneous velocity during high-speed movements. However, Johnston et al. (26) recently demonstrated a potential ceiling effect, whereby GPS technology sampling at 10 Hz demonstrated superior accuracy and reliability than a 15-Hz sampling frequency when measuring distance run at high speed. Interestingly, neither technology was considered to be valid when calculating peak speed; however, this may have been due to a limitation within the criterion measure itself (26). Consequently, GPS technology (i.e., satellite-based positioning) may be approaching its limits with regard to player-monitoring capabilities, paving the way for high-frequency inertial sensors to more accurately identify sports-specific movement patterns, such as in the current study.

Furthermore, previous research has revealed inconsistencies in reliability between microtechnology devices when comparing GPS-derived distance and speed measures (8,14,19,26,37), whereas research assessing "interunit" reliability in relation to inertial sensor–derived metrics, although scarce, has indicated more positive results (4,23), likely due to their self-contained nature (i.e., no reliance on satellite connectivity). These findings are in agreement with the current study where no differences in accuracy were found between microtechnology devices and suggests that assuming manufacturer calibration instructions are adhered to, and units are functioning correctly; our algorithm is highly accurate across multiple Catapult S5 Optimeye microtechnology devices and a variety of COD movement techniques (as each participant wore a different microtechnology device). This, however, requires further investigation, but may have important practical applications across a squad of athletes where the movement technique will likely differ between individuals.

The proposed algorithm requires inputs from each of the inertial sensors (accelerometer, gyroscope, and magnetometer) before undergoing a series of signal processing techniques to compute a "heading" or "yaw" angle, which subsequently enters a secondary custom-designed Canny edge detection algorithm to compute a precise COD angle. Canny edge detection is a gradient-based edge detection method often used in image processing to determine the level of variance between different image pixels with a goal to identify sudden changes in an image and identify certain objects (39). The algorithm presented in the current study uses a modified Canny edge detector to determine the level of variance or find transitions in the yaw angle signal derived from the inertial sensor inputs before hysteresis thresholding allows for the identification of "real edges," which are extracted and entered into a multilevel piecewise thresholding algorithm to calculate a precise COD angle. Importantly, the predetermined piecewise quantization thresholds can be manipulated, which has the potential to improve the accuracy of the angle change calculation and thus lead to greater optimization of the algorithm in the future. This is currently under investigation.

There are some limitations within the current study that must be acknowledged. Although only 5 participants were used, the primary measure of this study was based around the comparison between raw inertial sensor data and a high-speed video criterion; thus, the number of COD trials conducted is of most importance. The remotely piloted aircraft used in this study was able to be locked in position directly above the clearly marked COD point; however, it may be susceptible to very slight deviations during windy conditions, which could lead to a degree of parallax error within the high-speed video footage given the height of the drone (15 m) (35). Any trials where movement of the remotely piloted aircraft was deemed to have occurred were subsequently removed. Furthermore, given that the proposed algorithm is designed around a gradient-based edge detection method, it was not possible to precisely time-match the point at which the algorithm defines the "beginning" and the "end" of each COD trial with the high-speed video footage. Therefore, the 2-m distance either side of the COD center point was chosen based on visual inspection as a distance ensuring participants were "yet to commence" and had "completed" the COD in each trial, respectively. However, these limitations did not seem to have an effect on the level of accuracy displayed in the current study when comparing the proposed algorithm with the criterion measure, and in fact, this technology may offer a time-efficient, highly practical resource for field-based performance monitoring and analysis.

In addition, although future research using our algorithm to quantify COD angles at greater running velocities is warranted, we present an algorithm that has the capacity to operate at a commonly adopted, high-frequency inertial sensor sampling rate (100 Hz); and thus, we strongly suggest that any changes in running velocity will not impact the resultant COD angle calculation provided that the duration of an individual COD movement is not less than the time frame equivalent to this sampling rate (10 ms).

Although the current study utilized recreationally active males, we suggest that the proposed algorithm is highly applicable to team-sport athletes given the identical positioning of the microtechnology device seen during training and competition in a number of elite sports (Figure 3B) and the similarity in accuracy between participants evident in the current study. Although the proposed algorithm displayed a high level of accuracy for predetermined COD movements of varying angles, this study took place in a controlled environment and thus the focus of future research will assess the algorithm's performance during more dynamic, reactive, and unpredictable movement patterns typical of team-sport activity.

Practical Applications

Through this study, we have demonstrated an acceptable level of concurrent validity and a high level of accuracy and reliability in detecting, recording, and calculating a precise COD angle for predetermined COD movements ranging from 45° through to 180° (left and right directions), with low-level bias (less than $\pm 5°$). This novel algorithm has been designed using inertial sensor inputs, which have a much greater capacity (sampling hundreds of times per second in multiple axes) to measure more complex human motion than GPS technology when coupled with sophisticated signal processing techniques. Currently, the ability to extract, manipulate, and interpret these inertial sensor data into more practical and sports-specific metrics is viewed as a challenge (24), yet provides an opportunity for sports scientists to impart more advanced signal processing techniques on these extracted features and facilitate more in-depth analyses of the physical demands of numerous sports and communicate this critical information effectively to sports practitioners and coaches. The ability to automatically detect COD movements and accurately and reliably calculate a precise COD angle is something, to the best of our knowledge, which is yet to be quantified in a sporting environment and offers sports scientists, strength and conditioning practitioners, and athletes, an additional, nonlinear, sports-specific variable that may provide a new perspective to both acute and chronic load-monitoring practice.

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