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Agreement, Accuracy, and Reliability of a New Algorithm for the Detection of Change of Direction Angle Based on Integrating Inertial Data from Inertial Sensors

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Abstract: The development of algorithms applied to new technologies allows a better understanding of many of the movements in team sports. The purpose of this work was to analyze the validity, precision, and reproducibility of an algorithm to detect angulation of changes of direction (CoDs) while running, of between 45° and 180°, both to the left and the right at different speeds, in a standardized context. For this, five participants performed a total of 200 CoDs at 13 km/h and 128 CoDs at 18 km/h while wearing three inertial sensors. The information obtained from the sensors was contrasted with observation and coding using high-resolution video. Agreement between systems was assessed using Bland–Altman 95% limits of agreement as well as effect size (ES) and % difference between means. Reproducibility was evaluated using the standard error (CV%). The algorithm overestimated the angulation of 90° and 135° to the right (Cohen's d > 0.91). The algorithm showed high precision when the angulations recorded at 13 km/h and 18 km/h were compared, except at 45° to the left (mean bias = −2.6°; Cohen's d = −0.57). All angulations showed excellent reproducibility (CV < 5%) except at 45° (CV = 11%), which worsened when the pre-CoD speed was 18 km/h (CV < 16%). The algorithm showed a high degree of validity and reproducibility to detect angles during CoDs.

Keywords: validity; signal processing; wearable technology; change of direction

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1. Introduction

Changes of direction (CoDs) are one of the most common movements during soccer [1]. As studied by Martínez-Hernández et al. (2022) [2], approximately 20% of goals are preceded by a CoD in the English Premier League (EPL). In addition, [3] analyzed sprints in competition in ten EPL matches and showed that a third of sprints started from a non-linear action. Contextually, CoDs can serve as a transitional move between the offensive phase to create space and the defensive phase to pressure opponents or pull back [1,4]. From a biomechanical point of view, incorrect mechanics of a CoD could lead to injury to the knee's anterior cruciate ligament [5,6]. Pre-CoD angulation and speed are two variables that greatly influence the technical execution of movement, proportionally increasing muscle activation and load on the knee as the CoD is performed faster and at a more acute angulation [7]. If such variables can be quantified through portable technology and integrated into the load management model, performance improvement strategies as well as effort recovery strategies could be optimized.

Although different methodologies have been used to record changes of direction during competition, little information has been published to date [1,8–10]. For this reason, it is not easy to reach a consensus on how many CoDs a soccer player performs in a match, as well as the angulation that is performed. When the observational methodology was used, without considering the intensity of the actions, the number of CoDs recorded was very high, reaching 600 CoDs between 0 and 90° and 100 CoDs between 90 and 180° [1]. Using a similar observation classification, but distinguishing the actions into low and high intensity, the number of CoDs decreased, registering over 231 CoDs at 0–90° and 69 above 90° [10]. When a pre-CoD minimum speed of 4 m/s was established, the number dropped to 80 CoDs between 45 and 135° and 20 CoDs over 135–180°. On the other hand, with more modern technologies, new CoD registration methodologies have emerged during competition. The use of infrared laser (LiDAR), for the detection of CoDs in EPL players has shown a significant decrease in the number of CoDs in relation to observational methodology (~300–700 CoDs vs. 20–40 CoDs), with more CoDs recorded in the angulation of 120–180° [8]. However, both methodologies make it extremely difficult to approach the study of CoDs in a precise, immediate, and sustainable way, given the logistics and the number of people necessary to record the data and subsequently treat it.

Over the years, micro-electromechanical systems (MEMSs) that include inertial sensors such as accelerometers, gyroscopes, and magnetometers have served as an alternative for evaluating movement, enabling a quantitative analysis of the variables, as well as reinforcement between research and training [11–13]. Thus, there are several investigations that have shown acceptable precision identifying the turning angle during a CoD [14]. In this sense, the integration of three inertial sensors in what is known as an "Inertial and Magnetic Measurement Unit (IMMU)" has made it possible to obtain the spatiotemporal orientation of a body with greater precision, compared to when only one or two inertial sensors in isolation are used [15]. This has been possible due to the constant development of different algorithms and filtering steps, which have made it easier to merge the information obtained from the different sensors [15–18]. In a recent investigation, thanks to the information obtained from an IMMU and its processing by means of a specific algorithm, it was possible to be highly precise in detecting CoDs at different angulations, compared to high-resolution video recording [19]. To the authors' knowledge, only five studies have quantified CoDs during competition using inertial sensors, namely in players of basketball [20,21], handball [22,23], and soccer [24]. From our point of view, the number of studies related to CoD monitoring is low, although it is an important aspect of performance [25]. The scarcity of information on CoDs in sport could be related to the margin of improvement in the precision and reliability of the algorithms and calculations that are performed.

Therefore, the objective of this study was to determine the agreement and reproducibility of the algorithm in the detection of the angulation of changes of direction at different speeds, using the integrated information of several inertial sensors. The results of this study will demonstrate the ability of microtechnology to record the angulation of changes of direction in a standardized test.

This paper is organized as follows: Section 2 describes the instruments used, the signal processing, the test carried out by the participants, and the analysis used to obtain the results. Section 3 presents the results and Section 4 discusses the results. Section 5 concludes the paper.

2. Materials and Methods

2.1. Participants

The analysis was carried out using data from five non-professional athletes (age: 30.8 ± 2.1 years, height: 1.83 ± 0.03 m, body weight: 76.3 ± 4.7 kg), with experience in soccer. At the same time, all the participants had no health problems in the six months prior to the test. All subjects participated voluntarily, and the study was developed in accordance with the Declaration of Helsinki.

2.2. Instruments

The WIMUTM MEMS system (RealTrack Systems, Almería, Spain) and a high-resolution camera drone (DJI Mavic Pro, DJI, Shenzhen, China) were used to analyze the angles. The sensor used is presented in Section 2.2.1, the signal processing by the sensor in Sections 2.2.2 and 2.2.3, and finally the gold standard instrument is presented in Section 2.2.4.

2.2.1. MEMS System

A WIMU ProTM inertial device (RealTrack Systems, Almería, Spain), consisted of, among other components, a tri-axial accelerometer, gyroscope, and magnetometer with an adjustable frequency between 10 and 1000 Hz. The device weighed 70 gr, was 102 81 × 45 × 16 mm, and had an 8 GB internal memory (Figure 1).

Figure 1. Location of the WIMU devices with the use of the vests.

The devices were calibrated following the manufacturer's instructions prior to carrying out the test to, among other aspects, correct any alteration in the magnetic field that could influence the magnitude and direction of the vector [26]. In order to select the appropriate sampling frequency, a pilot study was carried out based on the performance of the test (Section 2.3). The data were recorded at a frequency of 1000 Hz. Using the WIMU ProTM 974 system software, a repeated analysis was performed on the same sample, changing the sampling frequency to 100, 500, and 1000 Hz. The results (registered angulations) were identical at those three frequencies, and 100 Hz was used for the purpose of maintaining the homogeneity in the sampling frequency as in previous studies [14,19].

2.2.2. Signal Analysis Process

Figure 2 summarizes the process from when the data is obtained until the reading is allowed.

Firstly, movement is detected through the inertial sensors that make up the device. The information recorded by the accelerometer, gyroscope, and magnetometer is saved in the memory stick. Once the activity is completed, the recorded data is downloaded to the software. Prior to reading the signal by the algorithm, it is possible to adjust the minimum CoD duration time (ms), the minimum peak intensity (G) at the moment of CoD, and a circular mean filter (%) which allows noise reduction. The algorithm used in the detection and calculation of the angles of rotation is directly implemented in the SPro "Change of Inertia" module, taking advantage of the modular system of plug-ins (Monitors) available with the software SPro 974. Each module accesses the data from the sensors/channels generated by each WIMU device. The algorithm obtains information from the data channels Euler X (subject's orientation degrees in respect to north) and Earth X, Y (components of acceleration on the horizontal plane in respect to the earth) using magnetometers (Figure 3a,b). Thus, the Earth X and Earth Y values are used to calculate the mediolateral and anteroposterior acceleration (Figure 3c). These accelerations are related to changes in footing or changes of inertia (COIs) by players. To make changes to the coordinate system of the horizontal acceleration vector (from the Earth coordinates to the subject coordinates), the Earth X and Earth Y data are re-projected using the Euler X channel data that had been calculated in the previous step, and the angle and module formed by the new vectors are calculated (Figure 3d). Once each COI is detected, an automaton-based unification algorithm is applied to identify multiple COI-type moves in a single CoD-type action.

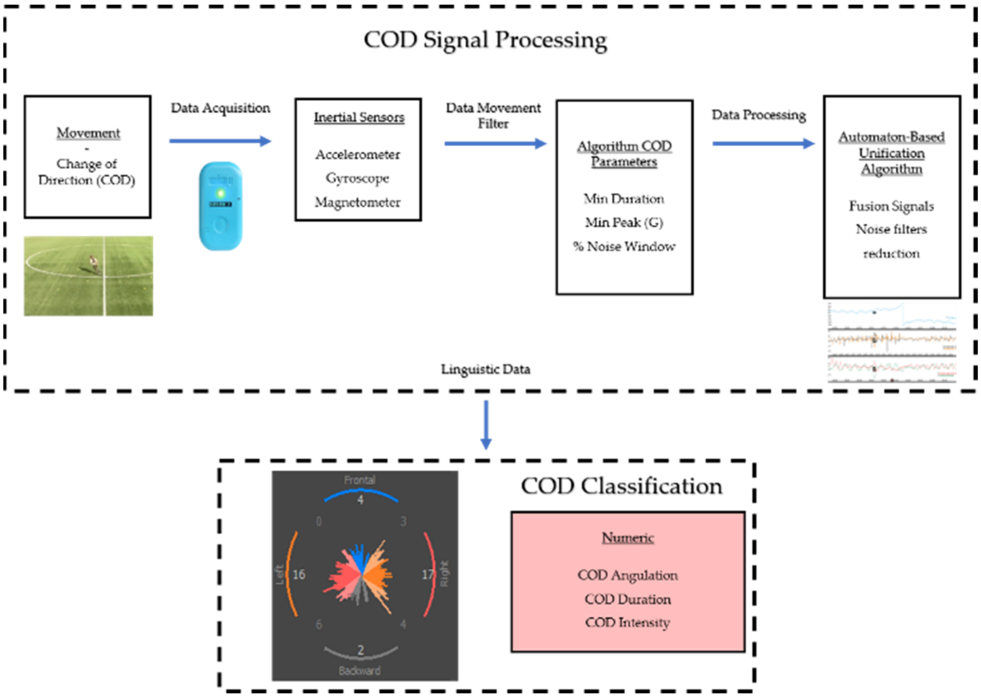


Figure 2. The principal steps of the proposed signals analysis for change of direction detection.

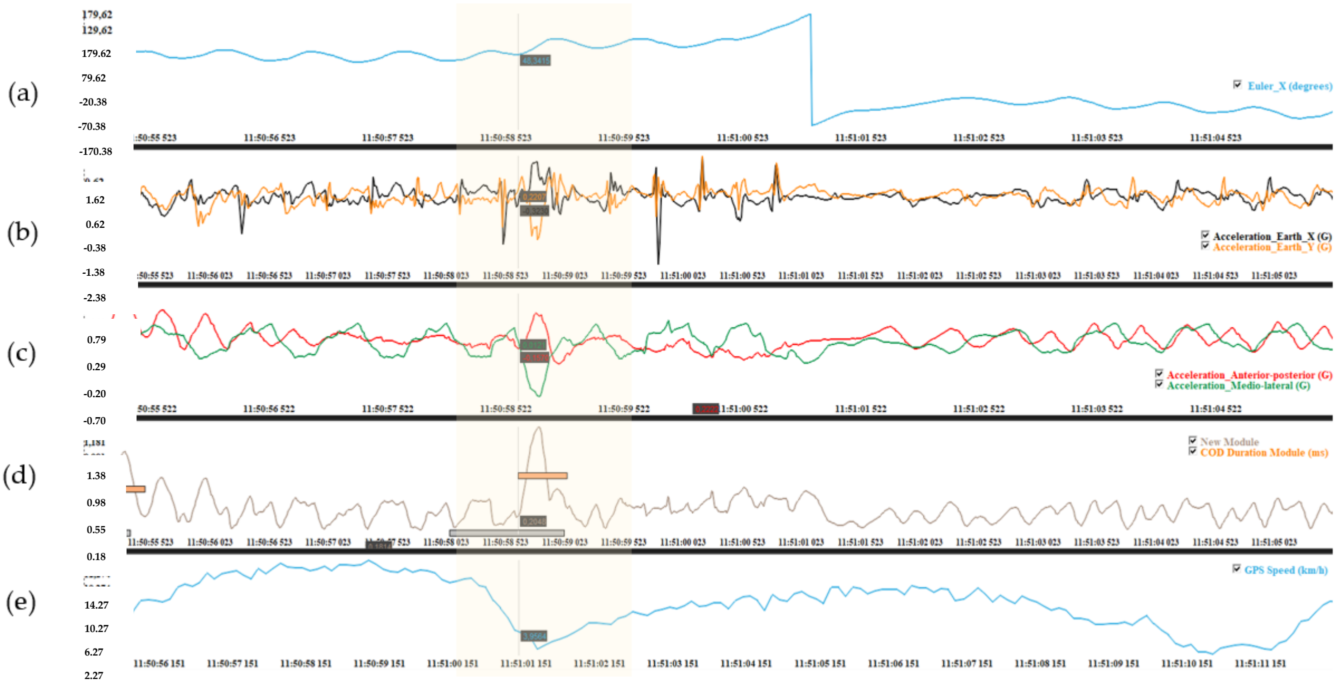


Figure 3. (**a**) Euler X data channel (degrees of orientation of the subject with respect to north). (**b**) Earth X and Y acceleration channels (components of acceleration in the horizontal plane with respect to the earth). (**c**) Conversion of Earth X and Y acceleration to anteroposterior and mediolateral acceleration. (**d**) New module formed from the anterior posterior and mediolateral signals, together with the CoD detected during the test. (**e**) Speed signal (km/h) from the GPS channel.

This is because a single CoD can be made up of several intense COIs, since several changes in footing may be necessary to make the desired change in direction. In this way, and considering the size of the module, the duration of the CoD (ms) is calculated. Finally, the orientation of the subject before and after the movement is analyzed to estimate the angle of rotation in the entry and exit direction of the CoD.

2.2.3. Pre and Post CoD Speed

The speeds of each of the actions were recorded via WIMU ProTM GPS technology devices (RealTrack Systems, Almería, Spain) for the test. Subsequently, using the WIMU ProTM system software (Realtracksystems), the speed was obtained two seconds before the moment of the CoD (Pre Spd (km/h)) as well as two seconds after the completion of the CoD (Post Spd (km/h)).

2.2.4. High-Resolution Camera

A drone (DJI Mavic Pro, DJI, Shenzhen, China) with a 12MP camera and 4K video recording was used during the test. To do this, it was placed 15 m above the breaking-away point, statically hovering over its position, thus ensuring a stable position throughout the test.

2.3. Procedures

In order to analyze the reproducibility of the device, each participant wore three devices on the intrascapular space on their backs (Figure 1). The devices were named from the inside out as IMMU1, IMMU2, and IMMU3. Prior to carrying out the test, and through a field test, it was checked that the devices were had been properly attached to one other.

For data collection, the same circuit used in the study carried out by Balloch et al. (2019) [19] was used (Figure 4). All participants wore artificial-grass football boots. To warm up, each participant performed a repetition at each of the selected angles for the test, that is 45°, 90°, 135°, and 180°, to the left (e.g., 45L) and to the right (e.g., 90R). Prior to carrying out the CoD, the participants had to walk fifteen meters in a straight line to the breaking point. The approach speed was supervised by means of a countdown by one of the researchers, with the participant having to reach the breaking point in three seconds when the speed was 13 km/h or five seconds for 18 km/h. In this way, an attempt was made to ensure a constant speed between all repetitions of the test. The test consisted in carrying out five CoDs towards each angle, both to the left and to the right, at a speed of 13 km/h (total participant = 40 CoDs; total group = 200 CoDs) and four CoDs at a speed of 18 km/h (total participant = 32 CoDs; total sample = 128 CoDs). With the purpose of avoiding possible fatigue-transfer to the technical execution of the CoD, there was a 60 s rest between each repetition.

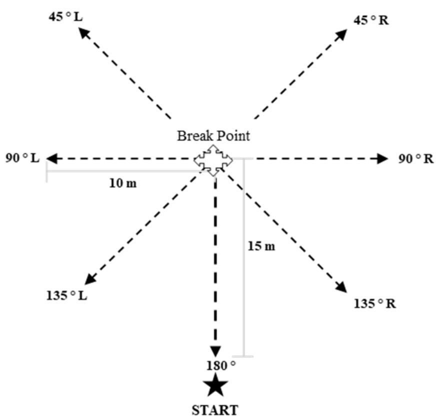


Figure 4. Circuit for testing. Used previously by the authors in [27].

Once the test was finished, the three IMMUs were synchronized using WIMU ProTM (Realtracksystems), seeking to correct any time delay in any of the devices. After this, and on the total acceleration channel, each of the test repetitions was selected. The algorithm was subsequently processed on these choices, using the SPro "Change of Inertia" module (Figure 3). For angle extraction through video recording, Kinovea® software (Kinovea, 0.8.15, http://www.kinovea.org/, accessed on 1 June 2022) was used. To do this, eight flat markers were placed on the ground of the pitch at each of the angulations two meters away from the breaking point. At the same time, the participant wore a white mark on their back, just above the devices. The angle was calculated using an angle measurement tool found within the software (Kinovea, 0.8.15), obtaining the angle from the measurement prior to CoD and after CoD, taking the two meters as reference (Figure 5). Fifteen repetitions were eliminated after observing a lack of agreement in the approach speed.

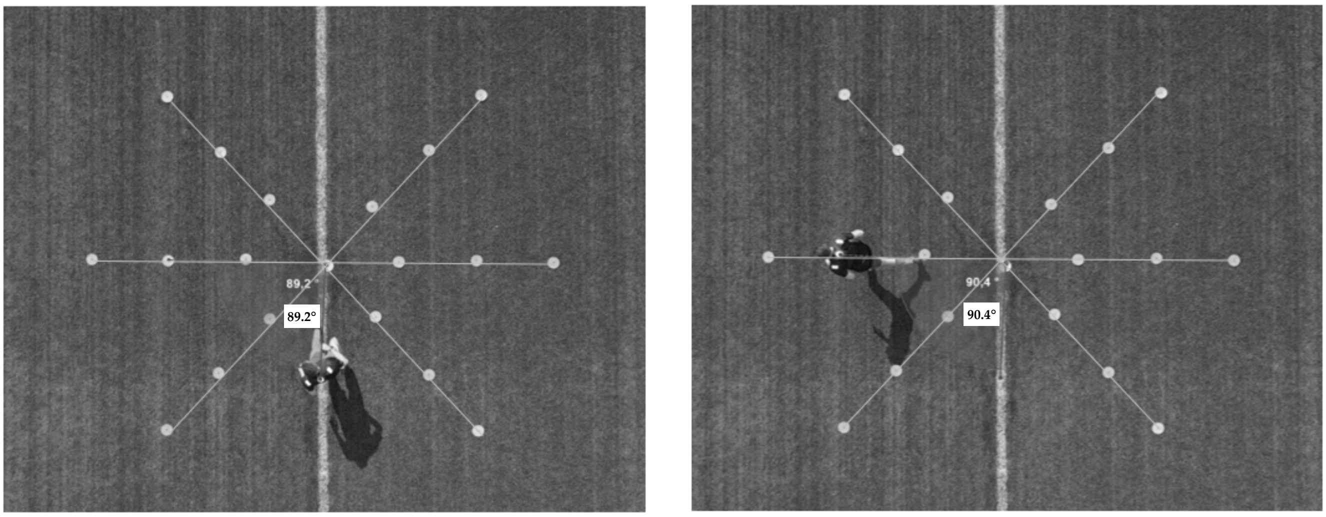


Figure 5. Example of a 90° left CoD during video analysis in Kinovea®.

2.4. Statistical Analysis

First, a descriptive analysis with mean and standard deviation was performed to describe the measurements obtained by the algorithm and video recording (Table 1). The agreement of the algorithm was evaluated using the Bland–Altman method [28], with a limit of agreement (LoA) of 95%, calculating the mean difference between the angle detected by the algorithm and the video recording at each angle (Figure 6). The percentage mean differences and the effect size between means of both instruments were also calculated, using Cohen's d, following the classification of Batterham A, (2006) [29]: trivial (0.2), small (0.2–0.6), medium (0.6–1.2), long (1.2–2.0), and very long (2.0–4.0). A one-way ANOVA together with the Games-Howell post hoc text was used to determine differences between the angulations recorded by both instruments at each angulation (Table 1). $p > 0.01$ was selected to mark the level of significance. To calculate the reproducibility of the algorithm, the %CV was used, where % < 10% has been defined as "poor" in the interpretation of reproducibility in the use of technology in sport [30]. A T test for paired samples, together with Cohen's d with a 95% confidence interval, and the Bonferroni post hoc test, were used to determine differences at each of the angulations at 13 km/h and 18 km/h (Table 2). A descriptive analysis was carried out with mean and standard deviation of the speed before and after CoD as well as the duration of the action (Figure 7a–c). Lastly, the effect size between the average recorded by each IMMU at each angulation was analyzed, as well as the mean differences (Table 3). All analyzes were carried out using Jamovi (V1.6.7.0, Sydney, Australia; The Jamovi project, 2021).

Table 1. Validity, reproducibility, and precision of the algorithm to measure CoDs at different angulations, compared to high-resolution video.

CoD Angle	Video Criterion (Mean ± SD)	Algorithm Criterion Mean ± SD	Mean Bias ± SD	% Diff	Effect Size (Cohen's d)	CI 95% (Lower/Upper)	CV (%)
45L	45 ± 2.7	44.1 ± 5.2	−0.9 ± 0.4	2.0	−0.21	−0.43/0.01	11.7
45R	46.2 ± 1.4	47.6 ± 4.8	1.3 ± 0.4	2.9	0.31	0.10//0.51	10.0
90L	90.4 ± 1.7	90.9 ± 3.1	0.5 ± 0.3	0.5	0.17	−0.02/0.37	3.4
90R	91.7 ± 1.1	95.0 ± 3.8 ***	3.3 ± 0.3	3.4	0.94	0.72/1.16	4.0
135L	140.2 ± 10.3	140.7 ± 4.0	0.5 ± 1.1	0.3	0.04	−0.14/0.24	2.8
135R	137.4 ± 1.2	143.2 ± 5.5 ***	5.7 ± 0.5	3.9	1.00	0.79/1.28	3.8
180L	181.8 ± 3.5	184.4 ± 5 ***	2.5 ± 0.5	1.4	0.47	0.26/0.68	2.7
180R	180.9 ± 2.4	182.7 ± 4.3 ***	1.7 ± 0.5	0.9	0.35	0.17/0.54	2.3

Note: *** $p < 0.001$.

Table 2. Validity, reproducibility, and precision of the algorithm to measure CoDs at different angulations at different speeds, compared to high-resolution video.

CoD (Angle)	Speed (km/h)	Mean ± SD	CI 95% (Lower/Upper)	Mean Bias (°) ± SD	Effect Size (Cohen's d)	95% LOA	CV (%)
45L	13	42.7 ± 4.7	(38.1/53.5)	−2.6 ± 1.1 *	−0.57	−1.01, −0.13	11.0
	18	45.3 ± 5.4	(37.3/54.9)				11.9
45R	13	47.7 ± 4.8	(37.0/55.7)	0.4 ± 0.9	0.07	−0.31, 0.47	10.0
	18	48.1 ± 8.4	(47.0/52.1)				16.9
90L	13	91.1 ± 2.9	(84.8/96.6)	0.4 ± 0.9	−0.18	−0.55, 0.17	3.1
	18	90.7 ± 3.5	(85.3/97.5)				3.8
90R	13	94.6 ± 3.9	(85.2/101.1)	−0.8 ± 0.8	0.45	0.08–0.81	4.1
	18	95.5 ± 3.6	(85.9/101.1)				3.7
135L	13	141.0 ± 4.4	(133.1/148.2)	0.5 ± 0.9	0.11	−0.28, 0.50	3.1
	18	140.5 ± 3.5	(134.5/147.8)				2.4
135R	13	143.6 ± 6.0	(142.2/146.6)	0.8 ± 0.9	−0.17	−0.21, 0.56	4.1
	18	142.8 ± 5.0	(135.7/153.2)				3.5
180L	13	184.6 ± 5.2	(175.5/194.5)	0.5± 0.9	0.10	−0.30, 0.50	2.8
	18	184.1 ± 4.8	(174.5/198.3)				2.6
180R	13	182.7 ± 4.6	(175.2/191.5)	0.14 ± 0.8	0.03	−0.33, 0.39	2.5
	18	182.6 ± 4.6	(175.3/191.6)				2.5

Note: * $p < 0.05$

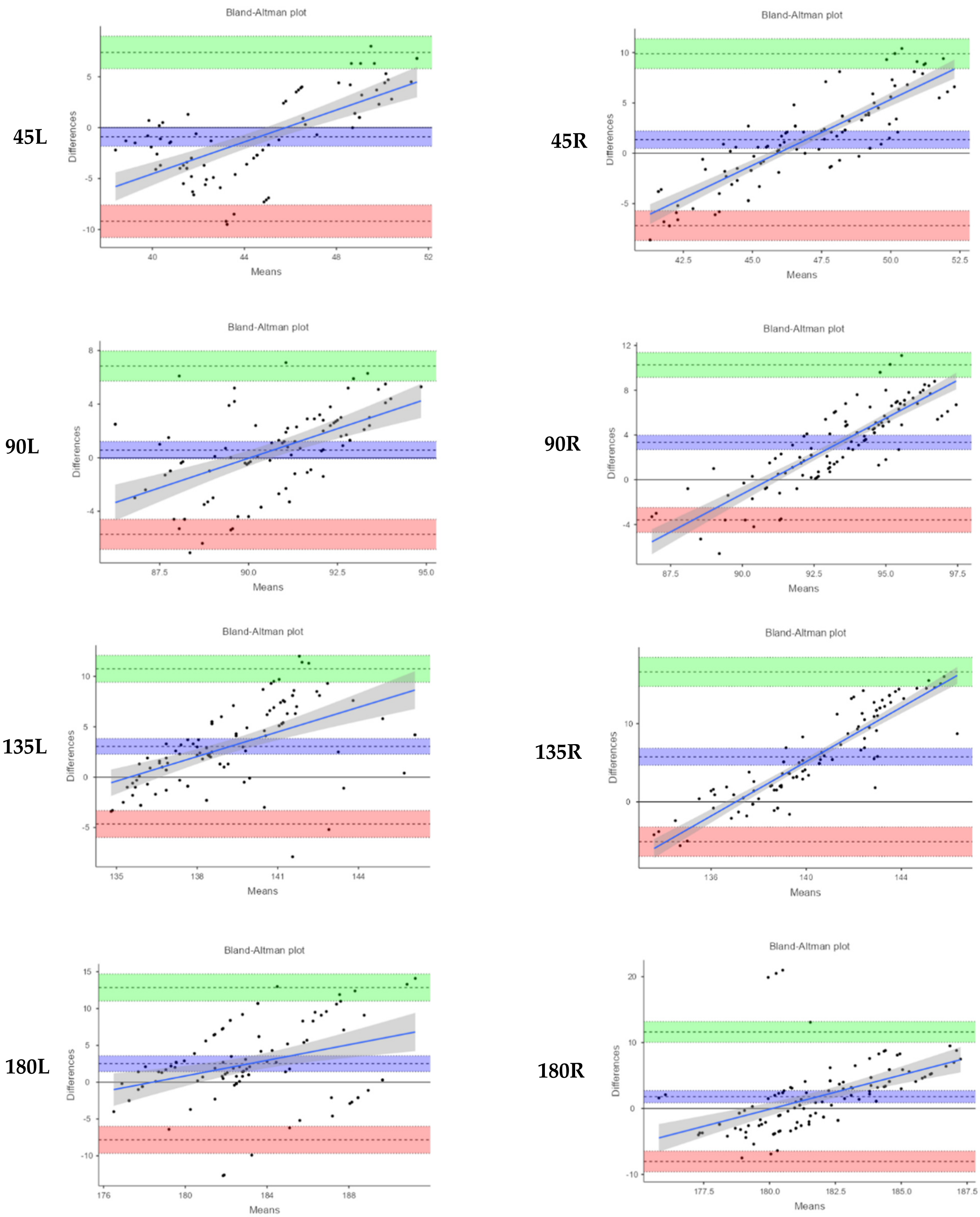
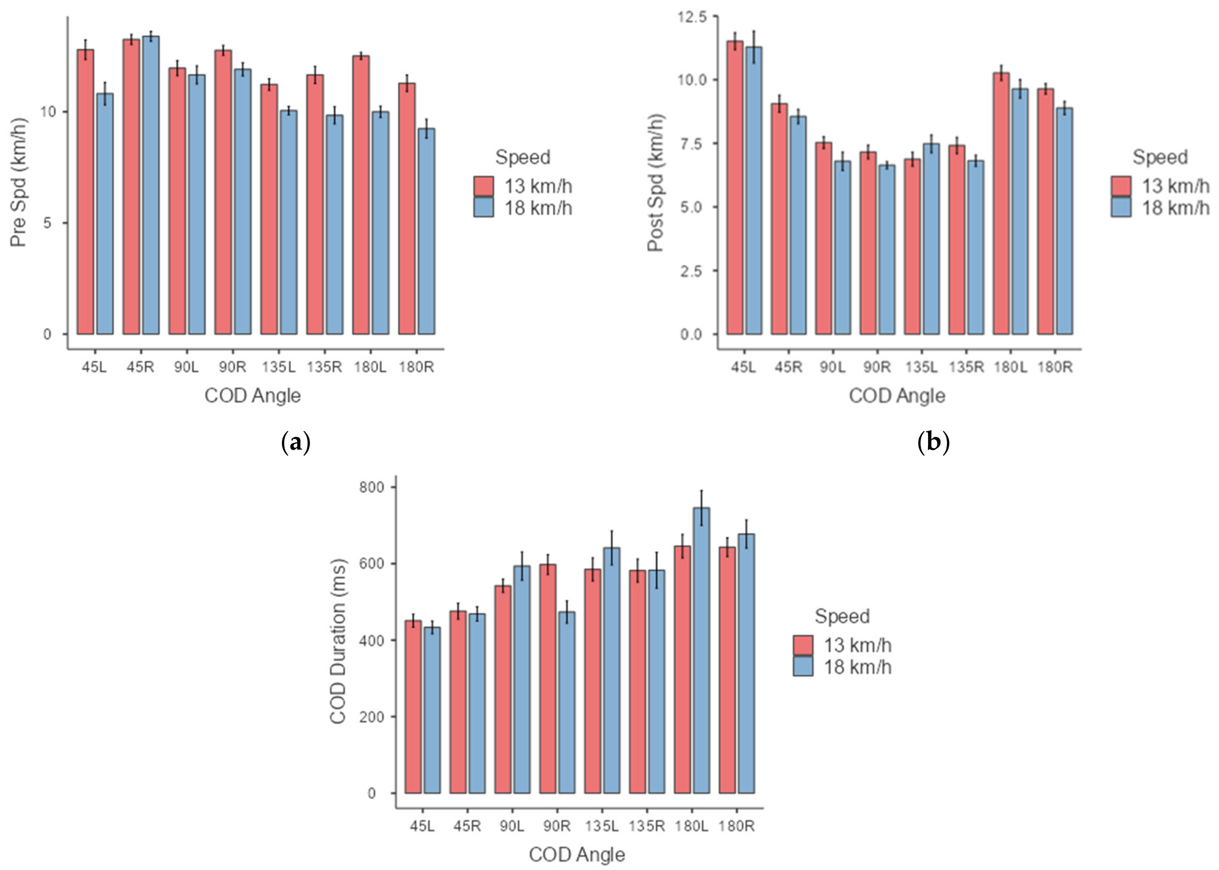


Figure 6. Bland–Altman calculation of the mean difference between the angle detected by the algorithm and the video recording at each angle. Mean % difference between the algorithm and the video (dashed line, blue zone), 95% confidence interval of the mean (blue zone), upper limit of agreement (LoA) of 95% (green zone) and lower limit of agreement (LoA) of 95% (red zone), mean line % difference (blue line), and confidence interval of the mean line % difference (shaded grey).



(**a**) (**b**) (**c**)

Figure 7. (**a**) Mean and SD of the pre-CoD speed at the different angulations during the test at speeds of 13 and 18 km/h. (**b**) Mean and SD of the post CoD speed at the different angulations during the test at speeds of 13 and 18 km/h. (**c**) Mean and SD of the duration of CoD at the different angulations during the performance of the test at speeds of 13 and 18 km/h.

Table 3. Reproducibility analysis of the three inertial sensors to measure angles during a CoD compared to high-resolution video.

CoD Angle	Sensor	Algorithm Criterion (Mean ± SD)	CI 95% (Lower/Upper)	Mean Bias (°)	Effect Size (IC 95%)	CV (%)	Mean Bias vs. Video Criterion (%)
45L	**IMMU1**	43.1 ± 4.3	41.3/44.9	IMMU1 vs. IMMU2 = −0.79	IMMU1 vs. IMMU2 = −0.17 (−0.71/0.37)	9.9	−4.4
	IMMU2	43.9 ± 5.2	41.9/46.0	IMMU1 vs. IMMU3 = −2.03	IMMU1 vs. IMMU3 = −0.44 (−0.97/0.08)	11.8	−2.5
	IMMU3	45.2 ± 6.0	42.9/47.4	IMMU2 vs. IMMU3 = −1.24	IMMU2 vs. IMMU3 = −0.27 (−0.79/0.24)	13.2	0.44
45R	**IMMU1**	47.8 ± 4.9	46.2/49.5	IMMU1 vs. IMMU2 = 0.98	IMMU1 vs. IMMU2 = 0.21 (−0.26/0.7)	10.2	3.3
	IMMU2	46.9 ± 4.5	45.1/48.6	IMMU1 vs. IMMU3 = −0.10	IMMU1 vs. IMMU3 = −0.02 (−0.49/0.44)	9.5	1.4
	IMMU3	47.9 ± 5.0	46.2/49.7	IMMU2 vs. IMMU3 = −1.08	IMMU2 vs. IMMU3 = −0.23 (−0.73/0.25)	10.4	3.5

Table 3. *Cont.*

CoD Angle	Sensor	Algorithm Criterion (Mean ± SD)	CI 95% (Lower/Upper)	Mean Bias (°)	Effect Size (IC 95%)	CV (%)	Mean Bias vs. Video Criterion (%)
90L	**IMMU1**	90.6 ± 3.0	89.5/91.7	IMMU1 vs. IMMU2 = −0.29	IMMU1 vs. IMMU2 = −0.06 (−0.56/0.43)	3.3	0.2
	IMMU2	90.9 ± 3.3	89.6/92.2	IMMU1 vs. IMMU3 = −0.63	IMMU1 vs. IMMU3 = −0.13 (−0.62/0.34)	3.6	0.6
	IMMU3	91.2 ± 3.2	90.1/92.4	IMMU2 vs. IMMU3 = −0.33	IMMU2 vs. IMMU3 = −0.07 (−0.56/0.42)	3.5	0.9
90R	**IMMU1**	95.5 ± 3.2	94.4/96.5	IMMU1 vs. IMMU2 = 0.46	IMMU1 vs. IMMU2 = 0.10 (−0.34/0.54)	3.3	3.9
	IMMU2	95.0 ± 4.3	93.6/96.5	IMMU1 vs. IMMU3 = 0.89	IMMU1 vs. IMMU3 =0.19 (−0.24/0.63)	4.5	3.4
	IMMU3	94.6 ± 3.8	93.4/95.8	IMMU2 vs. IMMU3 = 0.43	IMMU2 vs. IMMU3 = 0.09 (−0.35/0.54)	4.0	3.0
135L	**IMMU1**	140.5 ± 3.3	139.2/141.7	IMMU1 vs. IMMU2 = 0.01	IMMU1 vs. IMMU2 = 0.00 (−0.48/0.49)	2.3	0.2
	IMMU2	140.4 ± 3.9	139/141.9	IMMU1 vs. IMMU3 = −0.69	IMMU1 vs. IMMU3 =−0.15 (−0.62/0.32)	2.7	0.1
	IMMU3	141.2 ± 4.5	139.6/142.7	IMMU2 vs. IMMU3 = −0.71	IMMU2 vs. IMMU3 = −0.15 (−0.63/0.31)	3.1	0.7
135R	**IMMU1**	143.1 ± 5.5	141.3/145.0	IMMU1 vs. IMMU2 = 0.69	IMMU1 vs. IMMU2 = 0.15 (−0.35/0.65)	3.8	3.9
	IMMU2	142.4 ± 5.4	140.2/144.6	IMMU1 vs. IMMU3 = −0.63	IMMU1 vs. IMMU3 = −0.14 (−0.59/0.31)	3.8	3.5
	IMMU3	143.8 ± 5.6	141.9/145.6	IMMU2 vs. IMMU3 = −1.32	IMMU2 vs. IMMU3 = −0.29 (0.78/0.20)	2.9	4.4
180L	**IMMU1**	183.1 ± 4.2	181.5/184.8	IMMU1 vs. IMMU2 = −2.5	IMMU1 vs. IMMU2 = −0.55 (−1.05/−0.04)	2.2	0.7
	IMMU2	185.6 ± 4.7	183.9/187.3	IMMU1 vs. IMMU3 = −0.97	IMMU1 vs. IMMU3 = −0.21 (−0.71/0.28)	2.5	2.0
	IMMU3	184.1 ± 5.6	182.2/186.0	IMMU2 vs. IMMU3 = 1.53	IMMU2 vs. IMMU3 = 0.33 (−0.14/0.81)	3.0	1.2
180R	**IMMU1**	182.6 ± 4.6	181.1/184.0	IMMU1 vs. IMMU2 = −0.17	IMMU1 vs. IMMU2 = −0.03 (−0.49/0.41)	2.5	0.9
	IMMU2	182.7 ± 4.0	181.3/184.1	IMMU1 vs. IMMU3 = −0.16	IMMU1 vs. IMMU3 = −0.03 (−0.46/0.39)	2.1	0.9
	IMMU3	182.7 ± 4.4	181.3/184.1	IMMU2 vs. IMMU3 = 0.00	IMMU2 vs. IMMU3 = 0.00 (−0.45/0.45)	2.4	0.9

3. Results

Table 1 shows the means and standard deviations of the angulations recorded by the algorithm and the video recording. In relation to the agreement, all the angulations showed a difference of less than 4% between both instruments (Table 1 and Figure 6). However, the algorithm overestimated the angle in relation to the video, showing significant differences ($p > 0.001$), with a magnitude between small and medium, in four of the eight angulations. The 90R (3.3 ± 0.3°; Cohen's d = 0.94) and 135R (5.7 ± 0.5°; Cohen's d = 1.0) angulations were the angulations that showed the greatest difference between both instruments. In the rest of the angulations, the differences between both instruments were trivial. The algorithm showed good reproducibility in all angulations, except at 45L where reproducibility was poor (%CV = 11.7).

The one-way ANOVA analysis, as well as the post hoc Games–Howell test, only showed significant differences in the angle registered by the algorithm, when the test was performed at 13 km/h or 18 km/h at 45L, where the angle registered was greater than the speed of 18 km/h (mean bias = −2.6°; Cohen's d = −0.57) (Table 2). Precisely at this angulation, the reproducibility of the algorithm was poor at both speeds (CV = 11.0% at 13 km/h; 11.9% at 18 km/h). When the CoDs were performed at 45R and at a speed of 18 km/h, the algorithm showed the highest CV of all the combinations (CV = 16.9%).

Table 3 shows the mean differences and the effect size between the three devices at each angle. The results showed a high level of agreement when the angles recorded by each of the three IMMUs were compared, at all angulations, showing small differences in Cohen's d, only in two combinations of the 24 possible (IMMU1 vs. IMMU2 = Cohen's d = −0.44; IMMU1 vs. IMMU2 = Cohen's d = −0.55). At 45L and 45R the three IMMUS presented a poor coefficient of variation, but the same did not occur in the rest of the angulations, where all the IMMUS showed good reproducibility. The three IMMUs showed very similar differences based on the angle obtained by the video at all angulations. The 135R angulation was the direction that showed the highest percentage difference in the three IMMUs in relation to the video (mean bias = 3.9 ± 0.45).

4. Discussion

This work aimed to analyze the agreement and reliability of a new algorithm to measure angles during changes of direction at different angulations and speeds. The WIMU Pro device algorithm showed a high agreement and reliability to detect angles during changes of direction at different angles and speeds, in a standardized context, in relation to the video criteria.

The algorithm studied showed a favorable validation level (ES < 0.31) in 50% of the recorded angulations, while it overestimated the angulations of 90R, 135R, 180L, and 180R with respect to the video. However, it must be said that at a practical level the impact that these differences may have on decision making in sport seems irrelevant.

The results on the validity of the algorithm shown in the present study were very similar to those previously found by Balloch et al. (2019) [19], where the most significant mean difference was with 180L (mean ± SD = 4.9 ± 3.7°; ES = 1.36), while in the current work it was recorded at around 135R (mean ± SD = 5.7 ± 0.5°; ES = 1.0). At the same time, our results agree with other studies where the fusion of various inertial sensors was used to analyze angulation in sports, for example, to quantify the angulation and rate of turn during turns in swimming [31], to analyze the individual technique of skiers during a propulsive cycle in cross-country skiing, to measure the knee and trunk inclination during the descent in alpine skiing [32], or to analyze the rotation of the canoe in rowing [33].

Regarding the accuracy of the algorithm, our work, as in [19], showed relative differences of less than 5% in all angulations between the algorithm and the video recording. It is interesting to observe how the percentage difference did not increase, even after adding the 128 CoDs corresponding to the 18 km/h speed to the analysis.

On the other hand, the results showed a high degree of reproducibility of the algorithm at all angulations, except at 45L and 45R, where they were "poor" both at 13 km/h and 18 km/h (CV > 10%). This decrease in reproducibility could be related to the pre-CoD speed at 45°, especially at 45R, where the recorded speed was the highest of the entire test (Figure 7). These results coincide with those presented by Balloch et al., 2019 [19], where the highest pre-CoD speeds at 45R were recorded (14 km/h) as in this work (13.3 km/h); in both studies, there was also an upward trend of the CV (%) in relation to the rest of the angulations. More specifically, at 45° and at a speed of 18 km/h, the greatest variability of the algorithm was recorded (CV > 16%). This could be due to being left or right footed. In the present study, the dominant side of the five participants was the right. This was also the case in the study carried out by Konefał et al. (2022) [24], where 75% of the participants were right dominant, and it was observed that they veered more to the right than to the left during various small-sided games. In this way, there could be a relationship between laterality and experience or motor richness, and the need to brake less to turn towards their dominant side [34], and particularly towards angulations that are not very tight. This naturally coincides with the duration of the CoD (see Figure 7c), which increases progressively as the angle becomes greater. Only the 45L, 45R, and 90R angulations were performed below 470 ms, with 180L being the slowest, at an average of 745 ms; these data corroborate the hypothesis.

In relation to the differences in the agreement and reliability depending on the starting speed, it should be said that the algorithm was able to register angles with a similar precision, regardless of speed (13 and 18 km/h), and only showed significant differences at 45L (mean bias = $2.6 \pm 1.1°$). We can conclude that the speed variable did not "negatively" influence the ability of the algorithm to detect angulations, as in previous works [35]. These results reaffirm the suggestion made by Balloch et al. (2019) [19] that "any changes in running velocity will not impact the resulting CoD angle calculation", as long as the action does not last less than the time window marked by the sample rate frequency (100 Hz = 10 ms). In this way, and contrary to what happened with GPS technology [36–38], the precision of inertial sensors when recognizing the angulation of a CoD does not decrease as speed increases.

The data recorded by the three IMMUs reflect a similar behavior of the algorithm when applied to different devices of the same brand. A robust binding attaching all the devices during the test [39], as well as correct calibration of the inertial sensors prior to the test, could influence the results. These findings do not agree with those found by Buchheit, 2014) [40], where by using Global Positioning Systems (GPS) technology, a high variability among devices when recording high-intensity accelerations and decelerations (>4 m/s^2) during the same movement was found. In this way, inertial sensors together with specific filtering algorithms could be a useful alternative for the analysis of movements in sports.

This work is not exempt from limitations that must be taken into account when interpreting the results. In relation to the sample size, although only five participants were used, the main objective of this study was based on the comparison between the inertial sensor data and a high-speed video criterion; therefore, the number of repetitions performed is of the most importance. It would be essential to advance the understanding of the algorithm by analyzing precision instead of a standardized test in a real sports task. In this way, it would be interesting to assess the method in a real-game context, where its natural elements make the player's movement faster and more unpredictable. In addition, the fact that the study obtained its results from a standardized test means that the data should be used with caution when extrapolating them to real activities, such as training or competition matches.

5. Conclusions

As a result of the results, it can be concluded that the algorithm studied, in which several inertial sensors were integrated, can be a solution to detecting the orientation of a human body in a space [11]. The results showed a high agreement between the algorithm and the video, as well as among the IMMUs, at the angulations and speeds studied. In relation to reliability, the data collected at 45° should be used with caution given their low reproducibility.

In this sense, the fusion of signals from inertial sensors seems to be a valid alternative so that, together with the development of new algorithms, sports scientists can advance the analysis of the demands of sports. Integrating new potential into technological devices used daily in sports practice provides the opportunity to expand knowledge without adding cost to the company. In our case, quantifying the number and direction of direction changes could have great validity for physical trainers, in order to analyze the mechanical load in a non-linear movement.

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