Review of Smart Wearables Sensor-Based Techniques and Machine Learning for Change of Direction Detection in Sports

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Abstract

Change of Direction (COD) is a critical movement skill during athletic gameplay. In team sports like football, basketball, and rugby, the on-field performance is often assessed by the ability to change direction quickly. Optimizing the COD movement helps individual athletes reduce the risk of injury and improve skills, which results in better team strategy and outcomes. This review paper explores the algorithmic approaches investigated to date in the literature for detecting COD in athletes using wearable sensor data. Briefly summarize each algorithm's methodology and results, along with the strengths and weaknesses of their performance. An exploratory design methodology was used to search electronic databases like Google Scholar, PubMed, IEEE, and Science Direct, using predefined search phrases to identify relevant literature. The review demonstrated continuous advancements in COD detection. The review also highlighted the lack of standardized protocols for sensor placement, sampling frequency during COD movement analysis, and the limited availability of open-access datasets for COD movement, which leads to the low utilization of machine learning (ML) and deep learning (DL) models in automating the process of COD detection. Based on the identified limitations, we proposed a framework that uses Artificial Intelligence (AI) to automate COD detection. This review aims to improve COD movement detection with wearable sensors. It will help with informed decision-making and lay the groundwork for future research.

Keywords: *Accelerometer, Change of Direction, GPS, Sports, Wearable devices, Classification, Algorithms, Movement*

1. Introduction

Advances in sensor technology have transformed athlete performance analysis in sports through precise assessment of movement patterns, performance metrics, and biomechanical characteristics, which have replaced traditional observational methods (Migliaccio et al., 2024). The analysis of an athlete's sports performance depends on three main metrics, which include distance and speed measurements (Losada-Benitez et al., 2023), acceleration (Delves et al., 2021), and energy expenditure (Polglaze et al. 2016). These performance metrics deliver important information about athlete performance and training effectiveness, as well as fatigue monitoring and improvement opportunities. Athletes use agility to outperform opponents through their ability to dodge defenders (Young et al., 2022) and their quick movements to reach balls in football (Morral-Yepes et al., 2022) and their fast cuts to the basketball basket (Sugiyama et al., 2021). The essential athletic ability known as Change of Direction (COD) plays a vital role in complete athletic growth and injury avoidance and is essential for performance.

Sports scientists and researchers have studied the biomechanics and performance consequences of COD in various sports over the years. Neuromuscular adaptations (muscle activation and coordination) (Spiteri, Newton, & Nimphius, 2015), biomechanical factors (joint angles, balance, and ground reaction forces) (Spiteri, Newton, Binetti, et al., 2015), and metabolic demands (energy, power for quick bursts) (Jones & Dos'Santos, 2023), are involved in executing rapid directional changes across various sports disciplines. Athletes undergo rapid transitions from one movement pattern to another, requiring efficient deceleration, redirection of momentum, and acceleration in a new direction (Clarke et al. 2018). Biomechanical principles, such as speed, govern these movements (Jones & Dos'Santos, 2023), angle change (Dos et al., 2021), surface characteristics (Ismail et al., 2022) and individual athlete attributes. The research has shown that multiple high-intensity COD movements can lead to injuries such as hamstring injuries. (Bishop & Girard, 2013). With the proper training and exercise, results have shown to reduce the risk of injury (Siddle et al., 2024). The key challenge, however, lies in identifying when an athlete is at risk of injury, especially regarding their workload. If an athlete is performing more COD movement during a live competitive match than in practice sessions, they are generally at a higher risk of getting injured (Jiang et al., 2022). This highlights the importance of accurately identifying or classifying COD movements so that training loads can be managed better and reduce the risk of injury.

The two technologies that are widely used to capture and evaluate COD movement are Wearable devices and vision-based motion capture systems. Inertial measurement units (IMUs), a wearable device, are portable, cost-effective, and capable of capturing motion data in real time across various sports settings (Suo et al., 2024). On the other hand, vision-based motion capture systems, such as marker-based optical tracking or markerless camera setups, offer the advantage of nonintrusive measurement (Colyer et al., 2018). With these systems, athletes don't have to be in touch with any kind of sensor. However, despite their accuracy and minimal interference with performance, vision-based systems are often impractical for real-world, multi-player sports environments. Their high financial cost, complex setup requirements, and sensitivity to external conditions, such as changes in lighting, camera occlusion, and limited field of view, pose significant limitations. Moreover, these systems struggle with scalability when tracking multiple athletes simultaneously in large, open, or dynamic settings, making them less suitable for real-time use during live games or training sessions (Armanini et al., 2012; Keaney & Reid, 2018; Umek et al., 2016).

Wearable sensors such as accelerometers (which measure linear acceleration), magnetometers (which determine the direction and power of the magnetic field), and gyroscopes (which measure angular velocity) are commonly referred to as Inertial Measurement Units (IMUs). These IMU sensors can recognize complex details of athlete movements with high precision and accuracy (Chambers et al., 2015; Yang et al., 2024a). When integrated into various sports equipment, clothing, or body-worn devices, these sensors continuously monitor athlete activity during training or live games, providing performance feedback to athletes and coaches (Seshadri et al., 2019). Global Positioning System (GPS)-based wearable devices offer another way for capturing athletic movement activity using positioning data. But their effectiveness in specific environments, such as indoor sports, can be hindered due to poor connections (Cummins et al., 2013). Previously, different forms of human activity, such as sitting, walking, and standing, have been analyzed and classified using IMUs (Benson et al., 2018; Hou, 2020). Most of these studies have been done using the data collected from a controlled environment. Given that IMUs have already been used widely to capture and analyze movement patterns, they can also be used to capture COD movements during various sports activities (Alanen et al., 2021).

The data collected from these wearable sensors can then be used with different machine learning (ML) models to quantify and classify different human/athlete movements in different athletic environments. These ML algorithms analyze the datasets to identify complex movement patterns and learns to classify or predict the movement activity, and the results are shown in the form of performance metrics, which allows the development of different personalized training programs and early detection of injury risks (Bian et al., 2022; Demrozi et al., 2020).

1.1 Motivation

Sports is a rapidly growing industry that attracts millions in revenue and drives significant economic growth (Wang et al., 2022). This growth attracts much technology to enhance athletic performance and achieve better output by minimizing the risk of any injury and maximizing athletic potential (Haake, 2009). Due to this, the use of wearable sensors in sports has multiplied over the past few years (Fayed et al., 2024; James & Petrone, 2016). These sensors are used to analyze different athletic patterns, including COD. Given the importance of COD in athletic success, the detection, monitoring, and enhancement of this ability are crucial for coaches, trainers, and sports scientists (Martín-Moya & González-Fernández, 2022). Although previous reviews have analyzed the COD movement using IMUs, they have not explored the algorithms for detecting CODs, automating the COD detection using ML and deep learning (DL) models for real-time feedback, and reducing the dependency on other factors such as labor, time, and cost (Patil et al., 2024). The primary factor affecting automation is the lack of open-access data collected for COD events, which raises different ethical concerns in research. Whereas automation of general human activity recognition (HAR) using wearable sensors (IMUs, GPS) and smartphones through ML and DL techniques has been studied rigorously on the available open-access datasets (Gumaei et al., 2020; Gupta, 2021; Luptáková et al., 2022; Nayak et al., 2022).

This review explores recent advancements and limitations of COD detection algorithms and the use of ML and DL models in detecting COD movements using wearable sensors such as IMUs and GPS. The paper will offer a better understanding of the field and guidance for researchers and practitioners looking to select the most suitable algorithm for their specific application or develop more innovative solutions for COD detection.

To optimize training loads, prevent injuries, and improve athletic performance, accurate and automated detection of COD movement is necessary. So, with this study, by analyzing how wearable sensors and AI can help automate COD detection to provide real-time, cost-effective COD detection, we aim to address the gap in the existing literature.

By reviewing the current state-of-the-art algorithms designed for COD detection, the aim is to answer the following research questions:

RQ1. What are the techniques and advancements in COD detection algorithms using wearable sensors?

RQ2. What are the limitations associated with the existing techniques used for COD detection?

RQ3. How can AI be used to automate detecting COD movements to provide real-time feedback?

The rest of the paper is organized as follows: Section 2 defines the literature search methodology. Section 3 discusses algorithmic approaches based on IMU data, sensor fusion techniques, and GPS data. Subsequently, Section 4 discusses the findings based on the research question, based on the obtained results from all the algorithms. Section 5 proposes a framework for COD detection automation that has arisen from insights gained from the review. Finally, section 6 provides concluding remarks and future work.

2. Methodology

We used an exploratory design strategy to search and evaluate peer-reviewed studies in the field of COD detection with wearable sensors. The review was carried out in phases: identification, screening, eligibility assessment, and inclusion.

2.1 Eligibility Criteria

Included if all the following criteria were satisfied:

- Published in a conference or a peer-reviewed journal, and it has to be in English.
- Primarily focused on analysis or detection/classification of COD movements using wearable sensors.
- Studies must have used wearable sensors, including GPS and IMU, or can be a combination.
- Data must be collected from human participants doing physical activities.
- Detailed methodology of the algorithm must be presented.

Exclusion criteria were applied to:

- Non-peer-reviewed materials such as abstracts only, books, newsletters, reports, or encyclopaedia entries.
- Studies using other sensor types (video cameras, humidity sensors).
- Research involving non-human subjects or synthetic data.
- Studies focused on non-physical activities (cognitive, or emotional tasks, bio signal-only analysis without movement data).
- Articles lacking sufficient methodological details, including incomplete descriptions of datasets, algorithms, or evaluation processes.

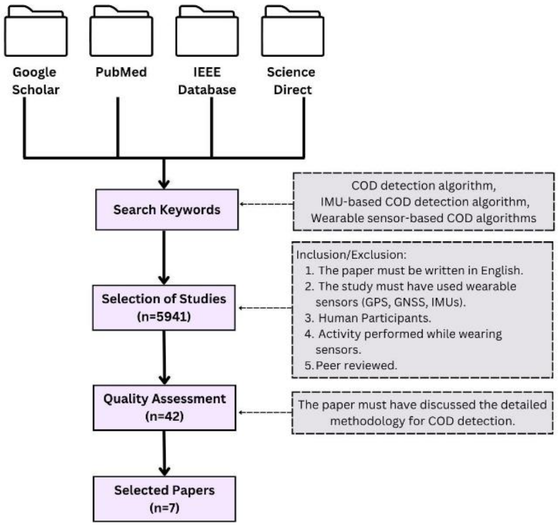

Figure 1. Article Search Methodology.

2.2 Information Sources

We have used different electronic databases to search the literature comprehensively: Google Scholar, PubMed, ScienceDirect, and IEEE Xplore. Given the very minimal research that has been done in the field of COD detection, we have not used any constraint on the publication date to ensure that all studies are covered.

2.3 Search Strategy

The combination of different search terms was used to select all possible studies. The following combinations were used:

1. "COD detection algorithm"
2. "IMU-based COD detection algorithm"
3. "Wearable sensor-based COD algorithms"
4. “Athletic COD Movement”

The search phrases were optimized according to the needs of each database. After searching the databases, this method gives a total of 5,941 research papers across all sources. Then, we have evaluated the titles and abstracts of each article to ensure that they have researched COD movement. Once the articles passed the first screening, we conducted a full-text assessment to check their compliance with inclusion/exclusion criteria. A total of 42 papers met all inclusion requirements, of which seven studies have presented a detailed framework for COD detection using wearable sensors, so we have included these studies for in-depth analysis (as depicted in Figure 1).

2.4 Data Extraction

For the final set of included studies, the following information was systematically extracted: authors and year of publication, type of physical activity and environmental setting, sensors used, number of participants and sample sizes, description of the COD detection methodology, analytical techniques employed, outcomes and performance measures, noted limitations and areas for future work.

This is the preprint version of the book chapter. The final published paper is available at the following link.

3. Related work

After reviewing the algorithms in the seven selected papers, this section provides a brief overview of the techniques used in the COD detection of each algorithm, its findings, and its limitations. First, we discussed the IMU-based algorithmic approach utilizing signal processing techniques, including an algorithm using gyroscope data, an algorithm using magnetometer data, and algorithms using multiple sensor data. Next, the COD detection algorithm based on GPS data is discussed. Finally, the sensor fusion techniques using IMU and GPS/GNSS data are discussed. Figure 2 shows the general overview of the process of COD detection using different techniques.

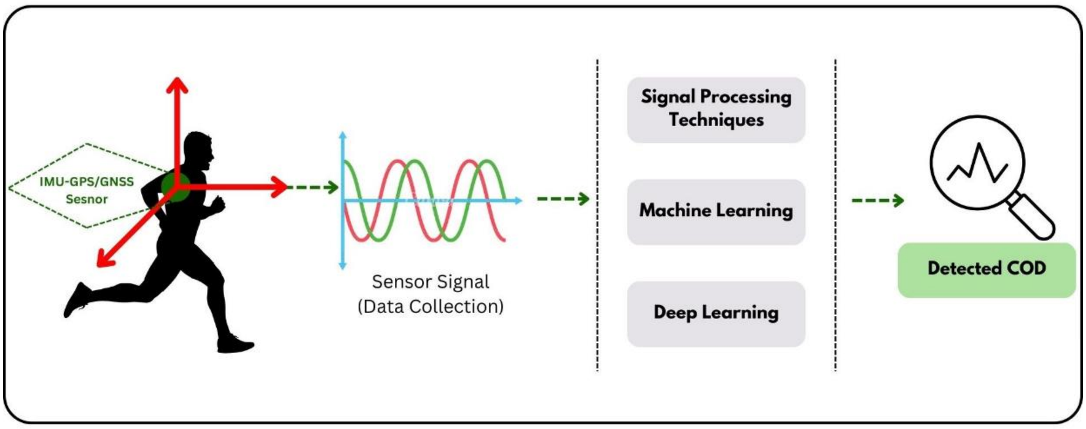

Figure 2. The process of COD detection.

3.1 COD detection using an Inertial Measurement Unit (IMU) sensor

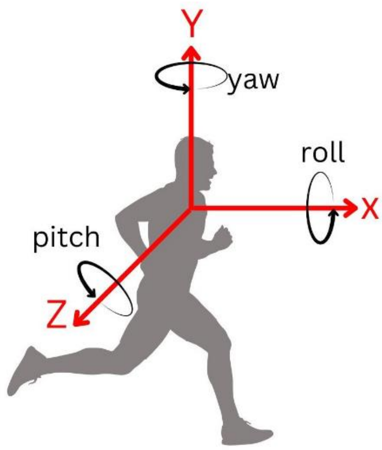

Figure 3. Pitch, roll, and Yaw angles represent rotations around the x, y, and z axes, respectively, describing the orientation of an object in three-dimensional space.(Meghji et al., 2019)

An IMU device typically combines multiple sensors to measure orientation, velocity, and gravitational forces (Kivikangas, 2022). It consists of a triaxial accelerometer, gyroscope, and magnetometer sensor. Due to their small and lightweight design, IMUs are considered one of the most preferred wearables during practice or live matches for real-time performance tracking and analysis. The triaxial nature of the IMU sensor is shown in Figure 3.

3.1.1 Gyroscope

The signal processing technique described (Harding et al., 2008) uses tri-axial gyroscopes to classify aerial acrobatics movements in elite half-pipe snowboarding. The gyroscope device used gives angular velocity data sampled at 100 Hz. An aerial acrobatics movement's Airtime (AT) is measured in seconds and calculated using an already developed method that uses accelerometer data, also sampled at 100 Hz (Harding et al., 2007).

The algorithm was designed using the basic concept of angular velocity. Angular displacement across each axis was determined by integrating the angular velocity data collected from the triaxial gyroscope. Then the angular displacement for each data point was added to obtain the total change in angle across a single axis. Now, to quantify the total change in body orientation that is COD movement, the total rotation across the three axes of the gyroscope was added to obtain the Air Angle. This value represents the total COD angle achieved in the air.

The algorithm (Harding et al., 2008) was tested on 10 participants' data from routine training and competitive snowboarding matches collected using a gyroscope sensor sampled at 100 Hz. The findings demonstrated that the signal processing technique reliably classified aerial acrobatics, mainly those revolving around a single axis. This allowed for categorizing the aerial movements into four groups of 180°, 360°, 540°, and 720° angles, respectively. The statistical analysis showed significant differences in the Air Angle measurements between all four angle groups, with mean differences and confidence limits providing a reliable classification of aerial acrobatics.

The limitation of using only the gyroscope for calculating the angle change or the COD angle is the drift error; if any error is present, it gets accumulated over time while integrating and turns into significant angle drift. Also, a gyroscope alone cannot distinguish between actual body rotation and vibrations, which makes them less reliable in classifying complex movements.

3.1.2 Magnetometer

Similar to the previous study, the authors (Fleury et al., 2007) used a triaxial magnetometer to detect COD movement, without mentioning the frequency or sampling rate of the sensor. The key component of this algorithm was filtering the raw signals, then identifying non-activity periods using standard deviation, and identifying COD events using Euclidean norms in the x-y plane with a predefined threshold. Rotations (heading or COD angle) can be expressed as Euler angles, rotation matrix, roll-pitch-heading, and quaternions (Kuncar et al., 2011). So, in this algorithm, the authors compute yaw angles using quaternions (which describe the composition of the three rotations) to enhance detection accuracy, ensuring precise orientation estimation.

To assess the algorithm's accuracy (Fleury et al., 2007), the author collected data from eight young, healthy volunteers, averaging 27 years old, who joined two experiments. First, volunteers were instructed to walk in a corridor, making ten 180° turns (five each way) and taking breaks in between. Then, to go up and down stairs, making four 180° turns (two each way) and eight 90° bends (four each way). The proposed method accurately tracked and classified their movements throughout both trials, demonstrating the effectiveness of using a tri-axial magnetometer to track COD in real-time by analyzing magnetometer signals in 2-second windows. However, the algorithm works well for 90° and 180° rotation angles, which can be improved further with more research, potentially improving COD detection accuracy. The authors have tested this method only for 90° and 180° angles, which leaves a significant gap in testing this algorithm in different COD angles. The major limitation of using a magnetometer for detecting COD is that the proximity of elevators or direct current engines significantly alters the magnetic field. This limits the magnetometer's reliability for tracking COD in specific environments.

3.1.3 Combination of multiple IMU sensors

The research (Meghji et al., 2019) developed an algorithm for detecting COD using triaxial accelerometers, gyroscopes, and magnetometer data. The process involves noise removal from the raw data and then calculating the heading angle using the gyroscope data. Magnetometer data is fused with the gyroscope for a more accurate yaw angle. However, as discussed in section 3.1.2, the magnetometer suffers from tilt error in the presence of external magnetic fields. They removed this error using roll and pitch angles derived from the accelerometer data. Then, the magnetometer data tilt error was corrected using these angles through rotation matrices (Kuncar et al., 2011) to align the readings accurately.

Authors (Meghji et al., 2019) have integrated more advanced signal processing techniques to identify the direction and more precise COD angles. A modified Canny edge detection algorithm (a multi-step process to determine the edges in the region of high-intensity change (Canny, 1986)) with a Gaussian filter to reduce noise in the yaw signal, analyzes the intensity gradient of yaw angles to detect sharp direction changes, performs non-maximum suppression to filter out unnecessary samples, and applies hysteresis thresholding to determine genuine edges based on a predefined threshold value. Finally, a multi-level piece-wise thresholding algorithm quantifies the angle precisely for each COD incident.

The wearable device Catapult OptimEye S5 is used in data collection. The algorithm demonstrated high accuracy in identifying and analyzing COD angles of 45°, 90°, 135°, and 180°. All angles showed the difference between the calculated mean COD angle and the intended COD angle in a range of -1.5 ° to 3.1°. With coefficients of variation (CVs) ranging from 2.0 to 4.8%, every angle showed outstanding reliability. Furthermore, for all angles, the algorithm's Typical Error (TE), or expected error, varied from 1.2° to 3.1°. Due to the high sampling rate of IMU sensors, they are prone to drift error over time.

Researchers designed a new study to evaluate the algorithm's validity, accuracy, and reliability while running (Balloch et al., 2020). The algorithm demonstrated good concurrent validity and high precision in detecting and determining the precise COD angle for various COD movements, ranging from 45° to 180°, in both left and right directions, with a low-level bias of less than ±5°.

To test the algorithm’s validity and reproducibility authors (Avilés et al., 2023) conducted a study to detect CODs at various speeds and angles to identify the most accurate combination of minimum peak intensity and signal smoothing. The findings demonstrated that the specific combinations of minimum peak intensity and signal smoothing were the most accurate for identifying CODs at various angles and speeds, suggesting adding filters to the algorithm according to the speed to detect CODs reliably.

Later, the author (Waqar et al., 2021) used accelerometer and magnetometer data to determine the COD angle. They documented this as a Tilt-Compensated Magnetometer (TCM) Algorithm, where they calculated the heading (yaw) angle using the magnetometer and corrected its tilt error using accelerometer data. They collected the IMU and GPS data using a wearable device to test the algorithm. The collected data have angles ranging from 45° to 180°. While testing the positioning accuracy, the algorithm completely diverged from the path while tracking a 45° angle and showed an error of 1.64±3.2 m in positioning accuracy for the entire track. This indicates that the algorithm is less reliable for minor angle deviations in the presence of noise.

3.2 COD detection using a Global Positioning System (GPS) sensor.

GPS, a navigation system that works on satellites, enables people to receive information about their position almost instantly anywhere on or near the Earth. GPS-enabled wearable devices can track physical activities, from outdoor sports performance to fitness tracking and navigation (Aughey, 2011).

The study (Gray et al., 2010) tested the validity and reliability of GPS sensors for measuring the distance traveled in field-based sports and showed that both path linearity and movement intensity impact GPS distance accuracy, decreasing reliability as intensity increases. Similarly, research (Alphin et al., 2020) tested the accuracy while sprinting. They compared the Maximum Sprint Speed (MSS) measured by GPS and Electronic Timing Gates (ETG). GPS had lower bias and error for the 80-meter sprint than the 30-meter sprint. Equivalence tests indicated that GPS measurements were within a 5% equivalence interval for short and long distances. Overall, GPS devices demonstrated acceptable accuracy for measuring sprint speed, making them suitable for COD detection and performance assessment in sports settings.

Authors (Reilly et al., 2021a) introduced a new variable called the 'GPS-COD' angle to automate the process of COD detection using GPS data. GPS data with a sampling rate (frequency) of 10 Hz is used. The data is segmented into 2.5-second intervals determined after careful observation of the GPS signal, containing 25 data points for effective data processing and feature extraction.

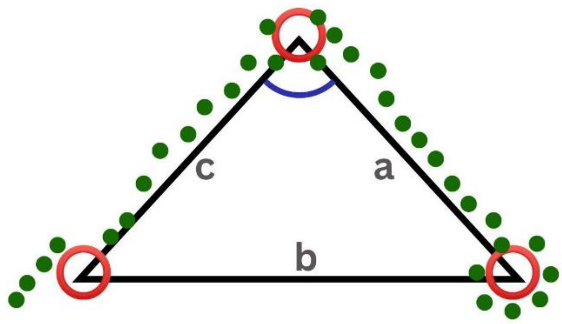

Figure 4. GPS-COD angle.(Reilly et al., 2021a)

Figure 4 depicts 25 green dots representing the complete movement of the player, i.e., the average value of 'Latitude' and 'Longitude.' Additionally, red circles denote the average location of the first 5 points, the median 5 points, and the last 5 points. The distance between these 3 points was calculated using the "geospatial location" of these points: a = distance between the second and third points, b = distance between the third and first points, and c = distance between the first and second points, forming a triangle shape for each 2.5-second interval. The blue angle represents the angle of interest, which is calculated based on the spatial arrangement of these points.

Then, the cosine rule was applied to calculate the COD angle marked in blue in Fig. 2. This gives us a GPS-COD angle variable for each 2.5-second interval, as shown in equation 1.

$$GPS - COD\ angle = 180 - \cos^{-1}\left(\frac{a^2+c^2-b^2}{2ac}\right) \quad (1)$$

To verify the predictive power of the variable, the authors tested the variable with a random forest classifier. The results showed that it could effectively predict COD events during gameplay. With an Area Under the Curve (AUC) of 0.957 and a standard error of ±0.01, the classifier demonstrated strong predictive power in automatically detecting COD occurrences throughout the game.

The study found a novel trigonometry-based method using GPS data to measure athletes' COD angles over 45°. After using this variable with a random forest classifier, this method demonstrated good reliability in classifying COD movements throughout the game with high accuracy. Overall, the authors provided an automated process for classifying COD events. The limitations that can be utilized for further research, such as the potential for error in classifying segments that do not have a COD movement as COD, the assumption that only one COD can occur in each 2.5-second segment, and different time windows (e.g., 1, 1.5, 2s) other than 2.5s, can be explored.

3.3 COD detection using sensor fusion techniques

IMUs are considered a gold standard for capturing motion-related information and are more reliable and better than GPS and the Global Navigation Satellite System (GNSS) (Buchheit & Simpson, 2017; Camomilla et al., 2018). However, GPS/GNSS offers positioning data. Utilizing this data with IMU data can provide essential information on athlete monitoring.

The study presents an algorithm using the sensor fusion technique (Apte et al., 2023), a macro-micro methodological approach designed to accurately detect and classify COD segments during the Agility T-test using data from a trunk-worn GNSS-IMU device. A camera recorded the COD activity as a ground truth to validate later results. The macro-analysis involves initiating movement by analyzing anterior-posterior acceleration data, utilizing filtering and wavelet decomposition to detect significant change points in the signal, such as local maxima and minima, and reconstructing the signal accurately. At the same time, the micro-analysis techniques focus on refining the detection of COD segments. GNSS ground speed is used to estimate completion time and validate against photocell data, enhancing the accuracy of the results.

This algorithm was tested across six participants who were randomly selected from 23 participants to assess their accuracy in detecting COD segments of order 90° and 180° and demonstrates an error (mean ± standard deviation) of -0.16 ± 0.22s for completion time estimation, 0 ± 0.66ms for COD detection, 3.5 ± 1.6% relative errors, and sequential movement duration of less than and 7 ± 7%. Although the algorithm performed well, the author (Apte et al., 2023) highlighted some limitations of this method, including improving synchronization between video and IMU by using clear markers like jumps or timestamps and higher video frame rates for better accuracy. Adding more sensors, like on the feet or sacrum, could provide more detailed data on ground contact and lower body mechanics. Finally, the methods must be tested on a broader range of athletes, including female players, to ensure they work for everyone.

Researchers (Waqar et al., 2021) introduced a new Particle Filter (PF) algorithm that combines IMU data with GNSS position data. This PF algorithm aims to accurately detect an athlete's COD and prevent divergence at each COD, a common issue with conventional PF algorithms (Arulampalam et al., 2002; Thrun, 2002). Initially, the algorithm detects COD events using the technique described in previous research (Meghji et al., 2019) using IMU data. After COD angles are categorized, the PF algorithm is initialized, which resamples the particles, assigns weights, and estimates the position using the samples and their weights. This approach has improved athlete tracking accuracy by up to five times compared to the TCM algorithm discussed in Section

3.1.3 (Arulampalam et al., 2002; Kuncar et al., 2016; Ozyagcilar, 2012; Thrun, 2002). Integrating IMU sensors with position data reduces the risk of drift error.

The algorithm's performance was evaluated using real-world IMU and GNSS data collected from athletes wearing wearable technology devices while running a predefined path involving multiple CODs. The algorithm exhibited an error of 0.32 ± 0.577m throughout the movement, with errors of 0.22 ± 0.32m observed during 45° COD movement, 0.18 ± 0.11m for 90°, 0.52 ± 0.41m for 135°, and 0.15 ± 0.08m for 180° while testing positioning accuracy. Additionally, the algorithm detects the direction of movement (left or right) and suppresses noise, resulting in higher accuracy. Although the algorithm displayed high accuracy while detecting different COD movements, testing this algorithm in free natural conditions is still required, as the authors only tested this algorithm in a controlled environment. Comparison of different sensor strengths and limitations is provided in Table 1.

Table 1: Comparison of wearable sensor modalities for COD detection.

Sensor Type	Sampling Rate (Hz)	Strengths in COD Detection	Limitations
Accelerometer	100	Captures linear acceleration, good for impact/load quantification	Sensitive to noise and gravity effects
Gyroscope	100	Direct measure of angular velocity, accurate for rotation	Drift error over long periods
Magnetometer	100	Provides an absolute orientation reference	Distorted by nearby magnetic fields
GPS/GNSS	100	Field positioning, movement tracking outdoors	Low resolution indoors, lag in high-speed COD

4. Discussion and findings

Our review paper investigated the algorithms for classifying COD movements using various signal processing techniques, IMUs, and GPS/GNSS sensors. We have provided an outline of the algorithms for COD detection and their outcomes in Table 2. It details the method, the type of sensor data they employ, the number of participants, and the kind of COD movement, thus providing a quick summary of the algorithmic approaches.

Table 2: Overview of reviewed algorithms, their method, and results based on sensors.

Paper	Year	Sensor	Subject	Method	Movement	Outcome
1.(Reilly et al., 2021a)	2021	GPS	23	Random Forest Classifier	Competitive football matches	GPS-COD angle as a strong predictor, AUC 0.975 ± 0.01
2. (Harding et al., 2008)	2009	Gyroscope	10	Signal Processing	Snow-boarding	Accurate and reliable classification around a single axis and classification into four groups of angles (180, 360, 540, 720).
3. (Fleury et al., 2007)	2008	Magnetometer	8	Signal Processing	Walk in a corridor and walk up and down the stairs.	Accurate classification of 90-degree and 180-degree COD angles.

4.(Meghji et al., 2019)	2019	Accelerometer Gyroscope Magnetometer	6	Signal Processing	Pre-determined COD circuit	Precise COD angles and good reliability with CVs in the 2 to 4.8% range. TE = 1.2 to 3.1 degrees.
5.(Balloch et al., 2020)	2020	Accelerometer Gyroscope Magnetometer	5	Signal Processing	Pre-determined COD circuit	Precise COD angles (45°, 90°, 135°, 180°), good reliability (TE = 1.6° ± 5.2°, CV= 1.3 ± 4.2 %)
6.(Waqar et al., 2021)	2021	Accelerometer Magnetometer	6	Signal Processing	Pre-determined COD circuit	Positional accuracy algorithm 1.64±3.2m during the whole track. There is less reliability in tracking small angles such as 45◦.
6.(Waqar et al., 2021)	2021	GNSS-IMU	6	Signal Processing	Pre-determined COD circuit	The algorithm accurately tracks athlete movement with an error of 0.33 ± 0.577m during the whole track. COD 45° = 0.22 ± 0.32m, COD 90◦ = 0.18 ± 0.11m, COD 135◦ = 0.52 ± 0.41m, COD 180◦ = 0.15 ± 0.08m
7.(Apte et al., 2023)	2023	GNSS-IMU	6	Signal Processing	Agility T-test	Error (mean ± SD): COD detection= 0 ± 0.66ms Completion Time estimation = 0.16 ± 0.22m

Based on the literature investigation, we have addressed our research questions related to the advancements and challenges in the algorithmic approach and the utilization of AI in COD detection.

4.1 What are the techniques and advancements in COD detection algorithms using wearable sensors?

Several techniques are used to detect athletes' COD movements. These algorithms were tested on different sensor data collected using different wearable sensors. The gyroscope measures angular velocity, so it is the primary sensor for calculating the heading or yaw angle (rotation around the axis) by integrating angular velocity over time (Harding et al., 2008; Meghji et al., 2019). Research (Fleury et al., 2007) demonstrated a magnetometer's effectiveness in classifying an athlete's COD movement. This method effectively identifies 90° and 180° angles when there is no disturbance in the magnetic field. Later, authors (Meghji et al., 2019) combined a gyroscope-derived yaw angle with a magnetometer sensor and accelerometer sensor to remove the issue of tilt error in the magnetometer for more accurate yaw angle detection and applied advanced signal processing techniques like Canny edge detection and piece-wise thresholding algorithms to detect COD angles more precisely and identify the direction of the COD movement. Study (Waqar et al., 2021) used sensor fusion techniques to mitigate the issues observed in the algorithm. In another study, authors developed an algorithm using position and IMU data, and the algorithm showed a fivefold improvement compared to the TMC algorithm (Meghji et al., 2019). A macro-micro analysis approach was presented (Apte et al., 2023) to quantify COD movements, identifying COD segments in the macro analysis, and for more accurate detection in the microanalysis. They then used GNSS data to measure the total completion time of the COD event. While tracking athlete activity using a GPS sensor can be challenging in indoor fields (Cummins et al., 2013), the authors (Reilly et al., 2021a) presented an automated method for high-accuracy COD event detection in outdoor conditions using a random forest classifier and fundamental signal analysis. The 'GPS-COD angle' variable using positioning data from GPS showed a good performance in classifying COD events. These improvements over time in detecting COD events using wearable sensors show the trajectory of advancement in this field.

4.2 What are the limitations associated with the existing techniques used for COD detection?

As discussed in the previous section, over time, there has been a continuous improvement in algorithmic development for COD detection, from the foundational algorithm designed in 2008 using a triaxial gyroscope, which calculates yaw angles by integrating the angular velocity data, to recent multiple sensor fusion techniques designed. Still, several limitations hinder the accurate detection of the COD movement, such as a high sampling rate, which leads to noise and drift error over time. Then, researchers began using GPS/GNSS sensor data with IMU data to reduce the noise and drift error. Given the low sampling rate of the positioning data obtained from the GPS/GNSS sensor, they are less prone to drift error.

Another major limitation identified is the improper placement of the IMU sensor across different studies. This creates variability in the datasets and reduces the reproducibility of the algorithm if the data is similar to the parent study. This highlights the lack of a universal standard for collecting COD movement data. Trunk-mounted sensors, usually placed between the scapulae with a vest, are the most common configuration due to their ability to approximate the center of mass movement. (Alanen et al. 2021). However, these can overestimate total body acceleration due to the movement of the vest itself. Other studies place IMUs on the lower back, thigh, tibia, or even embedded in custom knee sleeves to capture joint-level biomechanics (Rana & Mittal, 2020). For example, shank or foot-mounted sensors are ideal for identifying foot-strike events and impact forces during COD tasks. Regardless of placement, consistency and secure fixation are essential to reduce movement artifacts and maintain data integrity. The other challenge is the lack of standardized data collection protocols, including variability in sampling frequencies, sensor fusion algorithms, and filtering techniques (Alanen et al. 2021).

Moving ahead, the major challenge that was identified was the lack of an open-access dataset using wearable sensors, which affected the continued research in this field. In the literature, most studies have collected a minimal amount of data, and none of the datasets were made available publicly for further research and validation of the algorithmic approach. The reason highlighted for the scarcity of the dataset is the high expense and logistical problems associated with the data collection processes. Specialized wearable sensor technology is required for data collection, which requires extensive setup and trained staff. This specialized equipment can be expensive for individual use (Alanen et al., 2021). For example, high-quality data collection in sports often requires a controlled environment, like a sports or training facility, so that variables such as sensor calibration, athlete safety, and movement consistency are maintained (Balloch et al., 2020). Subsequently, the expense of those wearable devices and the skilled manpower required to operate and process the data extraction and storage made the collection of large-scale data financially burdensome. In combination, these factors impede the generation of extensive, diversified, and open-access datasets required for advancing research in sports performance analysis using wearable technologies. The limited availability of open-access datasets also affects the utilization of ML and DL models for automating COD detection.

The limited availability of the dataset also raises several ethical concerns:

- **Limited Reproducibility and Transparency:** When datasets are unavailable in the public domain to researchers, the study's findings cannot be easily replicated or independently verified. Indeed, this is an issue of a lack of transparency, as it discourages experimentation and replication, as other researchers cannot confirm or offer alternative interpretations of the findings using the same research data. On the other hand, ethics demand that the said findings be reproducible, meaning that any research that fails to reproduce any research finding in the absence of required data is considered questionable (Najjar, 2023).
- **Biased Research Outcomes:** The lack of diversity in datasets hampers good research. To put that in perspective, for example, even if the AI models have been intended for sports performance analysis, the training data originated from the athletes' regions, sports, or demographic groups. One can expect issues in the application of such models in another context. Such a lack of applicability increases bias, especially when empirical evidence, such as prediction outputs or contest judgments, is required (Najjar, 2023).
- **Lack of Standardization and Quality Control:** A lack of data leads to mismanagement and the inability to evaluate the standard of quality of data used. This could cause the use of poor-quality data, leading to invalid findings or incorrect models. Hence, concerns can be raised regarding the significance of the research results. On the contrary, access to many data types will lead to constant improvement in the structure and quality of the data, which is necessary to promote ethical scientific research (Najjar, 2023).

4.3. How can AI be used to automate detecting COD movements to provide real-time feedback?

Signal processing has been the backbone of the current COD detection methods, as reviewed in the literature. The state-of-the-art COD detection algorithm utilizes a sensor fusion technique; the PF algorithm is initialized, which resamples the particles, assigns weights, and estimates the position using the samples and their weights; it heavily relies on signal processing (Waqar et al., 2021). However, the application of ML and DL approaches has been underdeveloped in this domain. Although ML and DL approaches could probably support turning sensor data analysis into an automated feature extraction task with improved predictive accuracy, there are, however, a few reasons why these popular data analytics techniques have not seen such popularity in this discipline.

One of the primary limitations has been the availability of large, high-quality datasets needed to train machine-learning and especially deep-learning models (Gong et al., 2023). Deep learning, unlike traditional signal-processing methods, does not depend on a few rules and mathematical transformations but requires large data sets to learn complex patterns and make accurate predictions. Existing datasets are small, mostly from about ten participants, which is insufficient to train such models well. The rarity of such datasets is precipitated by the costs and difficulties in collecting sensor data in a controlled sports environment. Generalization across sports is another underexplored challenge; algorithms trained on soccer COD data may not transfer well to basketball or rugby, where movement angles, surfaces, and loads differ. Addressing these issues is vital for applied deployment.

Our review of existing literature found that the study (Reilly et al., 2021b) has presented an approach for detecting COD using AI, explicitly exploring machine learning algorithms. In contrast, authors (Jaiswal et al., 2025) compared the different ML and DL models for COD detection on the novel dataset. The results showed that both ML and DL models have similar performance in classifying COD events while running, but the dataset used was also relatively small, collected from only 7 participants. This shows that there is very limited development in utilizing AI for the detection of COD movement, as few studies have tried to automate this process. Whereas there have been numerous studies in the field of HAR, where authors have utilized different AI models to automate the process of classifying human activities like sitting, standing, running, and walking (Ramanujam et al., 2021; Sousa Lima et al., 2019; S. Zhang et al., 2022). Now these studies serve as a reference point for the development of a COD movement detection framework.

5. Conceptualization: Framework for AI automation of COD detection

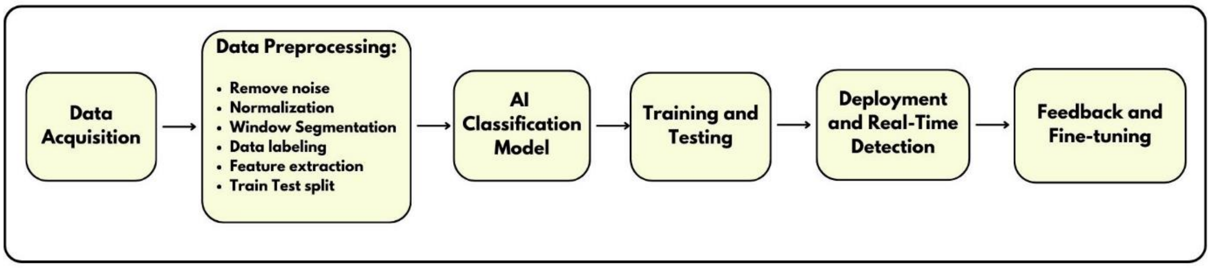

Figure 5. Framework for COD detection using AI.

Based on the insights from this review, we identified minimal utilization of ML and DL models in the COD detection field for various reasons, including the low availability of open-access datasets. To automate the process by leveraging the domain knowledge of HAR, we have proposed a framework, as shown in Figure 5, that can be utilized to enhance the COD detection process (Khatun et al., 2022; Najjar, 2023).

5.1 Data Acquisition

The first step involves collecting data from wearable sensors attached to the athlete's body, such as IMUs and GPS. Data should be captured in multiple sessions, and athletes performing different COD activities with varying intensity levels should be captured to ensure diversity and coverage. The dataset should also include real-world data from different live games to ensure broader applicability (Khatun et al., 2022).

5.2 Data Preprocessing

The next step involves preprocessing the raw collected data to enhance the quality and consistency of the dataset. During this step, several preprocessing steps can be performed on the dataset, such as noise filtering using techniques such as Butterworth filtering or wavelet transform, and normalization to ensure data is on a comparable scale across different sensors. After the normalization step, segment the dataset into a fixed-length window size using the window sliding approach (Banos et al., 2014). The next step involves labeling the segmented window to indicate whether a COD incident occurred, which is essential for training a supervised AI model. Although DL models automatically extract the features from the raw data, ML models require manual feature extraction for training. Different time and frequency domain features can be extracted from the segmented window data (M. Zhang & Sawchuk, 2012). Also, feature selection methods, such as principal component analysis, filter methods, or more advanced methods like bee swarm optimization metaheuristic and deep Q-network, can select the most relevant and essential features to reduce the computation load (Fan & Gao, 2021). The next step is to split the dataset for training and testing purposes (Khatun et al., 2022).

5.3 AI Model

The framework's core involves utilizing an AI model to detect and classify COD incidents effectively. ML and DL models can be used for this purpose (Gupta, 2021; Nayak et al., 2022). ML models such as SVM, random forest, and linear regression showed competitive performance while classifying general human activity. DL models such as CNN, RNN, and LSTM can sometimes outperform the ML models in terms of accuracy. Advanced DL models, such as hybrid or transformer models, have been shown to perform better in classifying human activity (Luptáková et al., 2022). A comparative review exploring all these models will be a better way to address the gap in this literature (Jaiswal et al., 2025).

The explainability of these AI models is also necessary to understand the factors responsible for identifying COD movements. Incorporating Explainable AI (XAI) into the framework for COD detection enhances system transparency, interpretability, and trust. Methods such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) help in identifying the most important or influential features that influence COD classification. For example, if coaches or athletes understand that deceleration and reacceleration are helping in COD classification, they can focus on these specific patterns more to enhance the COD performance (Novakovsky et al., 2022; Panigutti et al., 2020).

5.4 Model Training and Evaluation

Training the AI model involves using a labeled dataset to optimize the model weights. Regularization methods, such as dropout or weight decay, can be used to prevent overfitting. The model should be evaluated on separate validation and test datasets, using metrics such as accuracy, F1-score, and confusion matrix to assess its performance. Additionally, cross-validation can ensure that the model generalizes well across different athletes and sports contexts (Gupta, 2021).

5.5 Deployment and Real-Time Detection

Once the model has achieved satisfactory performance, it can be deployed to edge devices, such as smartphones or wearable microcontrollers, for real-time COD detection. Real-time feedback can be provided to athletes and coaches, enabling adjustments during training sessions or competitions (Gumaei et al., 2020).

5.6 Feedback Loop for Continuous Improvement

The next step in any well-implemented AI model is continuous fine-tuning, which updates and improves the model for real-world data. New data collected during training and competition can be labeled and used to fine-tune the AI model, adapting to changing conditions, new types of movements, or different sports. This iterative process ensures that the COD detection system remains relevant and accurate (Gumaei et al., 2020).

5.7 Implementation and post-implementation challenges

A series of challenges can be experienced while implementing the proposed framework for automation in COD detection. First, data quality is a fundamental issue because whenever data is captured through sensors worn on the athletes' bodies, the data might get affected by noise or distortion due to several factors, including the environment, the physical orientation of the sensors, or the athletes themselves. Robust preprocessing and filtering techniques are essential to ensure data reliability (Bangaru et al., 2020). Another challenge is integrating the different wearable systems with existing training systems. A standard method for collecting data, protocols for communicating data, and the system's architecture are required to achieve this. Real-time performance is crucial for providing immediate feedback. Still, it requires optimizing algorithms to balance computational efficiency and accuracy, which the limited resources of wearable devices can constrain (Nahavandi et al., 2022), so handling large datasets or running advanced machine learning models in real-time may require cloud-based solutions, introducing latency in data and connectivity issues (Yang et al., 2024b).

After the implementation phase, several problems arise, including scalability challenges and issues with system upgrades and maintenance. There needs to be the necessary infrastructure to scale the system for broader use across teams or facilities. Constant maintenance and user assistance are required to keep the system proper and efficient, together with the training of coaches and analysts to guide the best use of the system in practice (Carvalho & Sofia, 2020).

6. Conclusion and future work

In this study, we reviewed algorithms created to detect or measure COD movements using wearable sensor data. We highlighted the main principles of each approach. Our review showed a significant gap in research specifically focused on COD detection. While body-worn sensors like IMUs, GPS, and GNSS have been used more for analyzing athlete performance, only a few studies have applied them to COD detection, which shows that there is a huge amount of scope in this field. IMUs offer high temporal resolution and detailed kinematic information, making them suitable for detecting subtle movement aspects like penultimate foot contact, but they can be sensitive to where the sensors are placed and calibration errors. GPS and GNSS systems provide broader positional tracking and fit well in field-based team sports, but their lower sampling rates limit their ability to capture quick and detailed COD events. Machine learning (ML) and deep learning (DL) models show strong potential for COD classification. Traditional ML algorithms give clear outputs, while DL models perform better in complex situations with multiple sensors. However, most existing studies focus on planned COD movements, which limits how these models can be applied to reactive, in-game scenarios. More work is needed to automate the processes of COD classification/ detection using wearable sensor data with AI models.

6.1 Future Research Directions

In the future, more studies should explore hybrid sensor setups that combine IMUs with GPS/GNSS to leverage the complementary strengths of high-resolution kinematic data and field-level positional tracking. Novel ML/DL architectures, including attention-based models or multimodal fusion approaches, could improve detection accuracy for unplanned, reactive COD movements. Availability of open-access datasets collected specifically for COD movements in realistic sport contexts is needed to train and benchmark algorithms effectively, which is missing in the current literature. Additionally, investigating sensor placement optimization, real-time processing pipelines, and explainable AI techniques will help translate research findings into practical tools for coaches and support staff, enhancing performance monitoring and injury prevention strategies.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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