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Article

Design and data analysis of a wearable basketball training posture measurement system based on multifunctional conjugated polymer composite materials

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Abstract: Conjugated materials in basketball training are specific polymers included in sportswear to record and analyze player motions, helping to improve skills and prevent injuries by offering an in-depth analysis of the biomechanics and movements of athletes during training sessions. These materials provide basketball players with lightweight, long-lasting, and versatile qualities, offering comfortable gear that precisely monitors movements, complementing their training requirements for enhanced performance and technique improvement. This article describes creating and examining a novel wearable basketball conditioning posture assessment system called DMAS4B (Dynamic Motion Analysis System for Basketball). The technology includes sophisticated computer vision algorithms (CVA-Kalman Fusion Algorithm), Inertial Measurement Units (IMUs), and versatile, conjugated polymer composite materials. These materials, strategically positioned within specially developed sportswear, enable real-time tracking and evaluation of basketball player locations during training sessions. DMAS4B includes gathering detailed body movement data and focusing on essential basketball skills like shooting technique, dribbling stance, and defensive alignments. The collected data is delivered wirelessly to the MotionPro+ Basketball Analytics Software, a specialized platform for thorough analysis and visualization. The ability of IMUs, multifunctional conjugated polymer composites, and computer vision algorithms to work together to record and analyze basketball player movements precisely is demonstrated in this study. The system's implementation seeks to connect traditional training methods with advanced technology, providing athletes and coaches instant and thorough feedback on posture accuracy, balance, and mastery of techniques. The comprehensive examination of data collected from DMAS4B offers a novel method to improve basketball training programs, enhance player performance, and reduce the likelihood of injuries. In addition, the flexible character of this technology provides a foundation for possible use in various sports, transforming customised training methods worldwide.

Keywords: conjugated materials; dynamic motion analysis system for basketball; computer vision algorithm; inertial measurement Units; MotionPro+ basketball analytics software; basketball player's posture measurement

1. Introduction

Conjugated polymer composite materials are sophisticated substances created by blending conjugated polymers with additional molecules or materials. These composites have distinct qualities that arise from the inherent properties of conjugated polymers, such as being conductive, having optical activity, and containing semiconductor capabilities. By mixing these polymers with other substances or materials, like nanoparticles, carbon nanotubes, or an inorganic additive, the composite that results acquire improved features, such as better mechanical strength, electric conductivity, or sensitivity to external factors such as light or temperature variations. These materials are utilized in several industries, including electronics, sensors, optoelectronics, energy storage, and even specialised areas like wearable devices or biomedical implants, due to their versatility and ability to be tailored.

Carbon materials like CNTs are extensively utilised to create 3D-conductive networks in hydrogel matrices. These networks are necessary for establishing electron transport channels using π-conjugated structures and enhancing the mechanical characteristics of the materials. Carbon materials have appealing mechanical and electrochemical properties, such as a large specific surface area, strength, conductivity, and different surface functions [1]. Unlike electronically favourable cellulose nanocomposite material hydrogels, electronic conducting doubling network (DN) cellulose-based hydrogels usually consist of two interrelated polymeric networks with different mechanical properties. The harsh micro cellulose/running polymer network is an improved and advantageous integrated network that efficiently increases conductivity and disperses mechanical energy. In contrast, the soft polymer network maintains the integrity of the hydrogel during mechanical deformations [2]. Intelligent textiles and fibres have innovative features and can respond to various stimuli. The advancement of brilliant fibres and textiles is due to the combination of fabrics, chemical synthesis, materials science, electronics, information, artificial intelligence (AI), and various other fields [3]. Wearable, flexible electrical devices can adapt to the curved contours of human beings. They are created to track live human signals to the body, motion, and ambient data. These items are utilised for innovative personal wellness, amusement, and temperature control.

Zosimadis and Stamelos [4] introduced a portable gadget to monitor and assess athletes’ performance and health during sports activities. This wearable device, designed to be conveniently worn on the wrist, offers a comprehensive solution for tracking and recording essential biometric and activity information. It can track the skin’s temperature and heart rate, record arm movements, and recognise particular gestures using a built-in inertia measurement unit (IMU). This versatile device is used in various professional and recreational sports, making it an invaluable instrument for players and fitness enthusiasts [5]. The integration of wearable sensor technology with bionics is leading to advancements in other areas, such as individualised medical monitoring and flexible electronics, because of their excellent compatibility with the human body and wide range of sensing capabilities. The sensors were used as piezoresistive sensors capable of measuring enormous strains, making them suitable for applications in mobile electronics and soft robotics [6]. Piezoelectric sensing involves substances that can generate an electrical current when exposed to mechanical stress or pressure. Piezoelectric materials possess a property known as the piezoelectric effect, which allows them to convert mechanical energy to electrical power [7]. Saucier [8] focuses on examining the potential of soft robotic sensors (SRS) as an alternative to current motion analysis technologies, such as camera-based motion recording systems and IMUs. SRS generates an electrical evaluation (capacitive or resistance) that increases as the substrate is stretched. Li [9] explained the impact of electrode placement and pressure on the electrocardiogram (ECG) sensing capabilities of a technological textile (E-textile) wristband worn on the left upper arm. For showcasing, the study created a fabric arm sleeve with a CNT thin film on the electrodes to create an ECG-recognizing E-Textile system. The primary contribution of this work is discussed as follows：

To design and analyse an innovative wearable basketball training posture assessment system called DMAS4B technology, including sophisticated CVA-Kalman Fusion Algorithm, IMUs, and versatile, conjugated polymer composite materials.

To demonstrate the ability of IMUs, multifunctional conjugated polymer composites, and CVA-Kalman Fusion Algorithm to work together to record and analyze basketball player movements precisely.

To connect traditional training methods with advanced technology, providing athletes and coaches instant and thorough feedback on posture accuracy, balance, and mastery of techniques.

To improve basketball training programs, enhance player performance, and reduce the likelihood of injuries.

The proposed DMAS4B technology for measuring various postures of basketball players includes the following sections: Section 1 has an introduction and a literature review in Section 2; the design and analysis of the wearable measurement system are studied in detail in Section 3. The performed experiments and data analysis are addressed throughout section 4, and ultimately, the conclusion and future studies are given in section 5. The upper part of the human body plays a significant role in driving various areas of the body during basketball training, thereby providing additional information about body postures (shown in **Figure 1**).

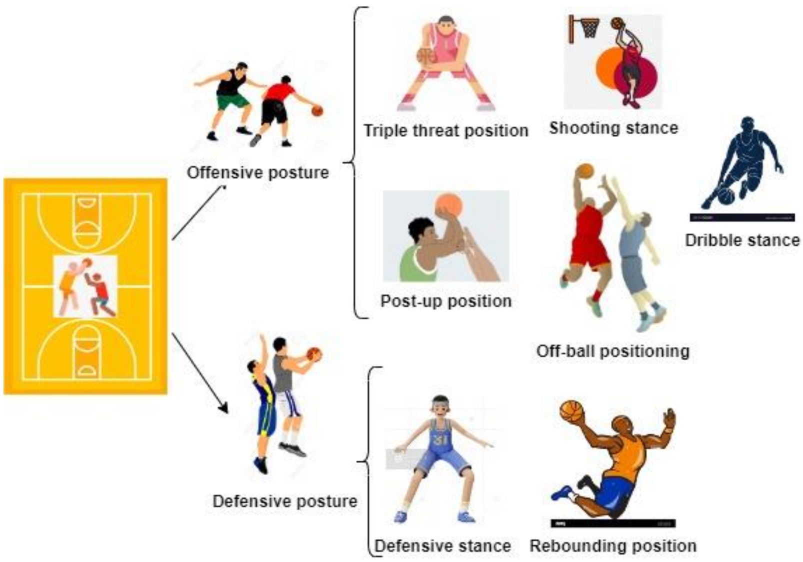


Figure 1. Several postures of basketball athletes.

Developing a range of basketball postures is vital for players to maximise performance. Every position corresponds to particular abilities, encouraging flexibility and adjustability. Understanding and embracing these positions leads to effective execution, strategic benefits, and injury prevention. Maintaining a steady posture control establishes a basis for dependable actions, which helps with team cooperation and determines the game’s speed. Adapting and changing strategies improves the interactions between individuals and teams, allowing players to make significant contributions during a match.

2. Literature review

Zhang et al. [10] examined the impact of image processing technology on basketball player postures; this article utilises the product traditional comparison method, data collection method, and equipment development method to gather samples and evaluate and create intelligent monitoring equipment with a simplified algorithm. Zhang et al. [11] focused on research into user demand, conceptual design of products, development of prototypes, and trials to determine dribbling posture.

Hou and Qi [12] proposed a system for monitoring basketball training posture that utilises intelligent wearable gadgets. The study investigates the attitude monitoring technology built upon these gadgets by examining the idea and categorisation of intelligent wearable devices. Jiang and Zhang [13] created a categorisation system for basketball posture. It then develops a hardware component to gather various posture data using motion sensors, extracting multiple-dimensional motion posture characteristics. Ren and Wang [14] focused on identifying the posture of the athlete’s body movement, specifically examining the posture of basketball players. Hou et al. [15] proposed an algorithm for recognising human gestures to verify different effects and motions of basketball players by tracking various activities in basketball. Tang and Guan [16] analysed the Convolutional Neural Network (CNN) multi-position wearable sensor for human activity identification utilised in basketball training. Furthermore, while preserving the current level of recognition, the primary training parameters are also decreased.

Worsey [17] proposed hardware requirements of motion sensors in different sports scenarios and methods for signal processing to extract useful information from the data. Zhao and You [18] proposed a wearable sports posture assessment system for rehabilitation athletes, focusing on sports and daily training. This system incorporates the technological advances of the Internet of Things.

3. Proposed methodology

Computer vision systems find it challenging to imitate the natural capability of the human eye to perceive different body movements precisely. Progress in technology for studying human behaviour is still in its early stages, limited by difficulties in obtaining data, dividing images into segments, processing in real-time, and developing robust recognition algorithms. Effective human detection relies on accurately identifying body positions and detecting postures, which directly affects the system’s performance. As explained above, intelligent wearables on the head and wrist assist in establishing accurate body alignment and monitoring posture, which is essential for improving system capabilities. **Figure 2** shows the overall proposed DMAS4B technique.

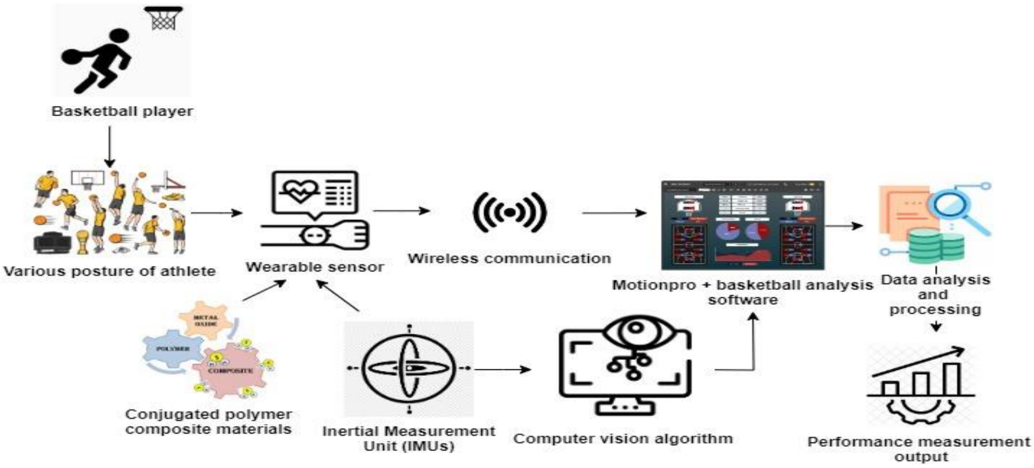


Figure 2. Proposed flow of DMAS4B system.

3.1. Material selection

Conductive polymers are beneficial for improving biosensors as they are excellent materials for fixing biomolecules. Conductive polymers and their mixtures are used in making different biosensors, improving the sensitivity and velocity of these devices. The quick spreading of the electrons through conducting polymers is advantageous for effective biosensors [19]. Conductive polymers provide a favourable environment for enzymes and biological molecules to be attached to the electrode's surface. Enzymes and biological molecules can be mixed in polymer films and deposited on electrodes using electrochemical methods. The enzymes that conduct polymers can be positioned close to the carrying out surface of the electrodes, thanks to their combination. This property makes them very suitable for the construction of biosensors. Glucose oxidase is an enzyme that can be efficiently utilised with the the polypyrrole films to detect glucose.

The biosensors utilising conductive polymers effectively delivered penicillin and identified different chromosomal diseases. A fast and effective flow injection method for measuring urea was devised employing polypyrrole films and a mixed polyion complex. Glucose biosensors identify glucose levels by immobilising glucose oxidase digestive enzymes using polymers. DNA biosensors using conducting polymer substances have been studied to diagnose and treat several diseases, including chromosomal issues, through repair, devastation, or expansion. Biosensors play a crucial role in overseeing the environment by regulating harmful substances such as formaldehyde and hydrogen peroxide that contribute to environmental deterioration.

3.2. Sensor integration in sports wear

Figure 3 shows the integration of basketball gears, conjugated polymers, and IMUs. The upper part of the human body plays a significant role in driving various areas of the body during exercise, thereby providing additional information about body posture. For this study, the workout regimen focuses solely on the thighs and arms. This research used four sensors to attach the upper and lower sensors. The information collected by the device's sensors was sent to the central station through the network. After receiving the data, the base station forwarded it to the upper computer using the serial port for further processing.

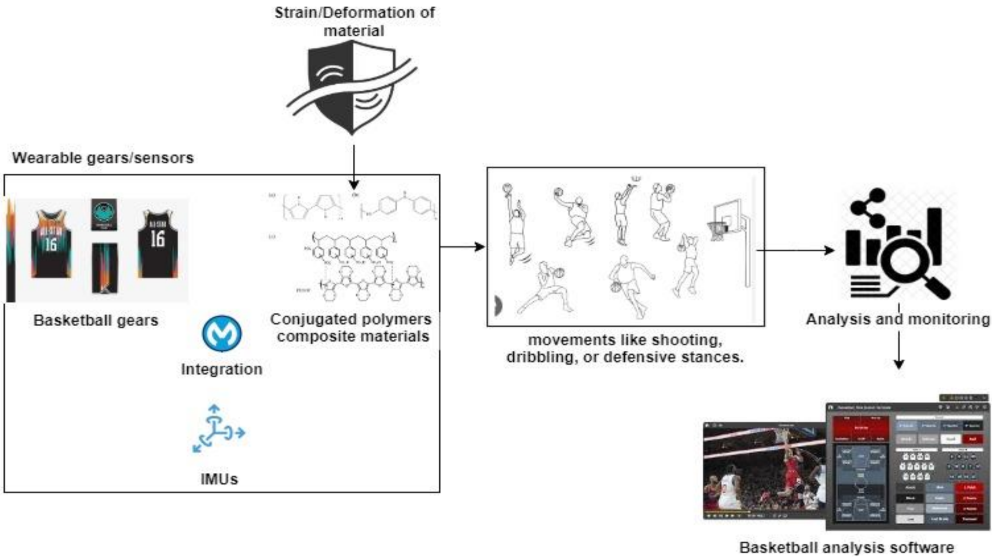


Figure 3. Integration of conjugated materials and IMUs in athlete's gear.

Accelerometers and gyroscopes are sensors that measure acceleration and angular velocity, respectively. They are essential for tracking motion and orientation.

$$a = \frac{F}{m} \tag{1}$$

$$\omega = \frac{\Delta\theta}{\Delta t} \tag{2}$$

The above Equations (1) and (2) show the acceleration and gyroscope, where a is the acceleration, F denotes force, and m represents mass; similarly, ω represents angular velocity increment, $\frac{\Delta\theta}{\Delta t}$ increment t is the change in the angle and time respectively. Sensor Fusion and Filtering: Integrating information from many sensors and implementing filtering techniques to enhance the precision of estimations. The equations of the Kalman filter are the foundation of a method that estimates the current condition of a system by merging measurements with predictions. Here is a more comprehensive clarification of each equation:

For prediction step,

$$\widehat{x_{k|k-1}} = F.\widehat{x_{k-1}} \tag{3}$$

From the above Equation (3), $\widehat{x_{k|k-1}}$ is the forecasted start estimate at time 'k', given observations up to k−1. k−1 represents the previous state estimate.

For covariance prediction,

$$P_{k|k-1} = F.P_{k-1} + F^T.Q \tag{4}$$

The above Equation (4) gives, $P_{k|k-1}$ is the estimated error covariance at time k, based on observations up to $k-1$. P_{k-1} is the error covariance from the previous iteration. Q reflects the covariance of the process noise, which considers the uncertainty in the system's dynamics.

For update step,

$$y_k = z_k - H.\widehat{x_{k|k-1}}(\text{Innovation}) \tag{5}$$

$$S_k = H.P_{k|k-1}.H^T + R\ (Innovation\ covariance) \tag{6}$$

From the above Equations (5) and (6), y_k is the residual or error in the measurement at time, $z_k$is the measurement collected from the sensors. H is the matrix that connects the state space with the measurement space. $S_k$is the novel covariance at time k. R represents the covariance of the measurement noise that indicates the level of ambiguity in the measurements.

$$K_k = P_{k|k-1}.H^T.S_k^{-1}(Kalman\ gain) \tag{7}$$

$$\widehat{x_k} = \widehat{x_{k|k-1}} +\ K_k.y_k(updated\ state\ estimate) \tag{8}$$

$$P_k = (I - K_k.H).P_{k|k-1}(updated\ covariance\ estimate) \tag{9}$$

All three Equations (7–9) shown above, K_k is the Kalman gain at time k, which determines the extent to which the forecast and measurement should affect the updated estimate. The revised state estimate at time k is represented by the $\widehat{x_k}$ symbol. $P_k$is the revised error covariance at time k. The equations depict the sequential procedure of forecasting the state, incorporating measurements, and enhancing the estimation in a Kalman filter. They offer a method to merge forecast and measurement data, considering uncertainties, to obtain a more precise estimate of the system’s condition.

Data Integration from Wearable Sensors: Gathering and coordinating data from different sensors to fully understand an athlete’s performance, as shown in the following equations. Merging data streams (for example, from accelerometers, gyroscopes, and heart rate monitors) given by the Equation (10) shown as

$$Fused\ data = w_1.Data_1 + w_2.Data_2 + \cdots + w_n.Data_n \tag{10}$$

Weighted average or fusion approaches (where w represents weights and $Data$ represents sensors data).

Motion Analysis and Position Tracking: Utilizing sensor data to examine movement, monitor locations, and evaluate approach. Tracking the position by using velocity and time given by following Equation (11) as,

$$Position = Initial\ position + Velocity\ \times Time \tag{11}$$

Wireless Communication and Data Transmission: Sending sensor data without wires to external devices or systems for analysis.

These ideas and formulas reflect the central components of sensor integration in sports clothing, including gathering sensor data, combining it, filtering it, analysing motion, and transmitting it wirelessly. These parts are essential for monitoring and enhancing athletic performance. The practical application entails customising these ideas to particular sensor categories, an athlete’s needs, and sporting situations.

3.3. CVA-Kalman fusion algorithm

Computer Vision Algorithms (CVA-Kalman Fusion Algorithm)—Kalman Fusion Algorithm is a subset of artificial intelligence that aims to enable computers to analyse and comprehend visual information derived from photographs or video data. Image processing methods in the CVA-Kalman Fusion Algorithm are essential for assessing and extracting useful information from visual data.

In the proposed study, the CVA-Kalman Fusion Algorithm is responsible for analysing visual data and extracting information from players' motions recorded by the conjugated polymer composite materials in the sportswear. The optical data could include details regarding body position, movement paths, or specific basketball actions such as shooting form, dribbling positions, or defensive formations. **Figure 4** shows the overall structure of the CVA-Kalman Fusion Algorithm for the proposed DMAS4B. On the other hand, Kalman filters could improve the accuracy of the estimated player motions based on the visual input. They could help accurately track these motions, accounting for any noise or imperfections in the readings acquired from the CVA-Kalman Fusion Algorithm.

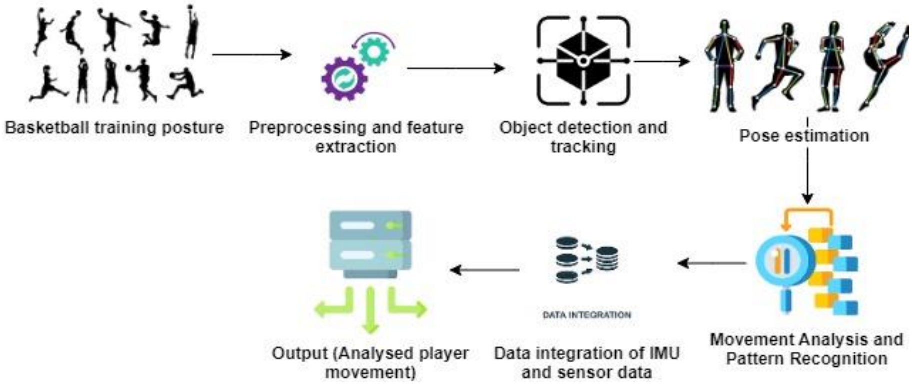


Figure 4. CVA-Kalman Fusion Algorithm for proposed DMAS4B.

The combination of Kalman filters and CVA in this basketball training system can enhance the precision and dependability of the collected data, offering coaches and athletes more precise observations on posture accuracy, balance, and technique mastery. The application of Kalman filters would vary depending on the data acquired from the conjugated materials, the features of the measurements, and the specific purposes of the analysis or tracking in basketball training.

3.3.1. Basketball training posture

This section contains the starting input to the algorithm, which is the unprocessed visual data recorded by the Computer Vision Algorithm (CVA). The optical data includes details about basketball players' movements captured by the conjugated polymer composite materials integrated into the sportswear. This information might contain specifics like body posture, courses of movement, and particular basketball activities such as shooting technique, dribbling stances, or defensive arrangements.

3.3.2. CVA-Kalman integration algorithm

Its importance inside the DMAS4B system may be better grasped by reading about the Computer Vision Algorithm (CVA-Kalman Fusion Algorithm). By seamlessly merging optical and sensor data, the CVA-Kalman Fusion Algorithm is aimed to increase the accuracy of recording basketball players' motions. An algorithmic part dealing with computer vision analyses video feeds from cameras placed all around the practice pitch to glean crucial details on the whereabouts and motions of the competing players. After that, it's coupled with data from the Inertial Measurement Units (IMUs) built into the competitors' gear. The CVA-Kalman Fusion Algorithm block combines Computer Vision Algorithms (CVA) with Kalman filtering. This algorithm is created to merge the advantages of both methods to improve the accuracy and reliability of the gathered data. The system analyses the unprocessed visual input from CVA and uses Kalman filters to enhance the precision of estimated player movements. This combination seeks to offer coaches and athletes more dependable observations on the accuracy of posture, balance, and mastery of technique.

3.3.3. Kalman filter

The Kalman filter is a key component of this fusion process, which forecasts and adjusts the players' predicted positions and velocities using the incoming data. The Kalman filter enhances tracking accuracy by using mathematical modelling to correct for inaccuracies and noise in the visual and sensor data. This supplementary method allows the DMAS4B system to maintain precise and reliable movement tracking even in dynamic training environments with rapidly changing player locations. The CVA-Kalman Fusion Algorithm elucidates the system's operation, which enhances its capacity to track and evaluate the performance of athletes. The Kalman Filter block is a mathematical technique that analyses the visual input from CVA. It is specially made to decrease noise and measurement errors, leading to a more precise estimation of player movements. Kalman filters are commonly employed in tracking applications to improve data accuracy by considering observations' uncertainties and flaws.

3.3.4. Data processing and feature extraction

Regarding basketball training, the CVA-Kalman Fusion Algorithm for data processing, and adaptable conjugated polymer composites. The Kalman filter handles raw visual input, improving accuracy and eliminating interference, preparing the data for analysis. Paired with the MotionPro+ Basketball Analytics Software, the device provides a comprehensive analysis of precise body movement information, which helps optimize training regimens, boost player performance, and prevent injuries. The flexibility of this technology indicates possible uses in many sports, transforming personalized training methods worldwide. Within the DMAS4B system for basketball training, feature extraction involves finding and separating particular features or properties from the collected data. In this situation, the characteristics obtained are probably connected to the complex motions and mechanics of basketball players throughout their training sessions. A few possible features are:

Analysis of Shooting Technique: Identification of factors associated with shooting mechanics, such as the location of the arm, angle of release, and follow-through, which offer valuable information about the player's shooting ability.

Evaluation of Dribbling Stance: Characteristics related to dribbling motions, such as footwork, body position, and hand coordination, help assess and improve dribbling abilities.

Defensive Formations: Identification of characteristics associated with defensive positions, sideways movements, and response speed, providing useful information for evaluating defensive abilities and planning defensive tactics.

Player Location Tracking in real-time: Functions that allow for accurate tracking of a player's position on the court, delivering live spatial data essential for analyzing player motions during drills and exercises.

Balance and Posture Metrics: Identification of characteristics associated with balance and posture precision, providing information on the player's stability and body control during different movements.

The extracted features contribute to a thorough comprehension of the player's performance, enabling focused feedback on particular parts of their game. The DMAS4B system, with its combination of inertial measurement units (IMUs), conductive polymer composites, and computer vision algorithms, collectively operates to analyze and extract these characteristics, improving the analysis offered by the MotionPro+ Basketball Analytics Software.

3.3.5. Improved player movement data output

The Enhanced Player Motion Data Output block represents the outcome of the CVA-Kalman Fusion Algorithm. This output contains improved information on different elements, such as posture precision, stability, and mastery of technique. The improved data offers coaches and athletes more accurate observations, which helps them make better judgments during basketball training sessions. To summarise, the diagram shows how raw visual data is processed step by step using the CVA-Kalman Fusion Algorithm. It demonstrates how each block helps improve and enhance player motion data in the DMAS4B system. The following code (Algorithm 1) illustrates an athlete's motion tracking using DMAS4B.

Algorithm 1 Pseudocode for tracking athletes' motion

```
Procedure AnalyzeBasketballPlayerMovements (Data from DMAS4B):
  Initialize Variables and Data Structures
    # Receive and preprocess data from DMAS4B
  InputData = ReceiveDataFromDMAS4B(Data)
  PreprocessedData = PreprocessData (InputData)
  # Analyze individual player movements
  For each Player in PreprocessedData:
    PlayerID = Player. ID
    PlayerData = PreprocessedData [PlayerID]
        # Analyze shooting technique
    ShootingAnalysis = AnalyzeShootingTechnique (PlayerData.ShootingData)
        # Analyze dribbling stance
    DribblingAnalysis = AnalyzeDribblingStance (PlayerData.DribblingData)
        # Analyze defensive alignments
    DefenseAnalysis = AnalyzeDefensiveAlignments (PlayerData.DefenseData)
        # Combine analyses into a comprehensive player report
    PlayerReport = GeneratePlayerReport (ShootingAnalysis, DribblingAnalysis,
 DefenseAnalysis)
    # Display or store player reports
    DisplayPlayerReport (PlayerReport)
    StorePlayerReport (PlayerID, PlayerReport)
    # Generate overall training session report
  OverallSessionReport = GenerateOverallSessionReport (PreprocessedData)
    # Display or store overall session report
  DisplaySessionReport (OverallSessionReport)
  StoreSessionReport (OverallSessionReport
End Procedure
```

The above pseudocode describes a process called "Analyze Basketball Player Movements" for monitoring athletes' movement using data from DMAS4B. It sets up variables, receives and prepares data, and then examines individual player motions. This involves evaluating shooting form, dribbling position, and defensive positioning. The evaluations are merged into player summaries, which can be shown or saved. The process ends by creating a comprehensive training session report, which is then displayed or stored as needed. Pseudocode offers an organized, language-neutral representation of the logical flow and operations of an algorithm.

3.4. MotionPro+ basketball analytics software

The MotionPro+ Basketball Analytics Software is designed for the DMAS4B system, which receives wireless data on player movements. It uses IMUs and computer vision algorithms for thorough analysis, examining aspects such as firing technique and protective alignments. Coaches and players gain advantages from immediate evaluation of performance, getting prompt feedback on posture and skill in technique. Adaptable observations enable personalized examination depending on training goals or athlete requirements. Originally created for basketball, MotionPro+ demonstrates the ability to be used in several sports, highlighting its versatility. MotionPro+ serves as a link between the raw data of DMAS4B and important insights, helping to provide a comprehensive understanding of player movements, performance, and skill improvement in basketball training. **Table 1** shows the experimental setup.

Table 1. Experimental setup.

Parameter	Description
Participants	30 basketball players (15 male, 15 female) aged 18–25 years
Skill Levels	Varying skill levels: beginners, intermediate, advanced
Duration of Training	6 weeks
Training Frequency	3 sessions per week
Session Duration	90 min per session
Control Conditions	Control group of 15 participants using traditional training methods without the DMAS4B system
IMU Sensor Module	Bosch BNO055
High-Speed Cameras	GoPro HERO8 Black
Processing Unit	NVIDIA Jetson Nano
software	MotionPro+
Algorithm	CVA-Kalman Fusion Algorithm

3.5. Experiments and results

Dataset

The information is somewhat outdated now, as it comes from the original tracking data collected between 2013 and 2016 (the NBA made the data unavailable to the public on the 23 January 2016) [20]. The shot routes were simulated using standard LOESS methods (the locfit tool in *R*, specifically). The *x*, *y*, and *z* paths were each represented individually as an expression of time, using a "span" of 0.05. The most challenging aspect is determining when shooting in motion starts. When the ball's horizontal velocity towards its destination reaches its highest point. The concept here is that this is the moment when the participant has chosen to begin moving the ball again towards their body. The shooting motion dataset used by NBA players undoubtedly has precise data on shooting mechanics, such as release time, velocity, and angle, considering the current status of basketball training. Using similar metrics, trainers and coaches may analyse and improve their athletes' biomechanics—and their shooting form, accuracy, and consistency. In keeping with modern data-driven approaches in basketball training, they may modify training programs to improve certain aspects of a player's shot by evaluating motion data [21,22].

4. Tracking accuracy

Position deviation: This metric calculates the average difference between players' positions as reported by the system and their actual positions throughout basketball actions. From a mathematical perspective, it can be expressed as Equation (12) below,

$$Positional\ deviation = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_{actual,i} - x_{recorded,i})^2 - (y_{actual,i} - y_{recorded,i})^2} \quad (12)$$

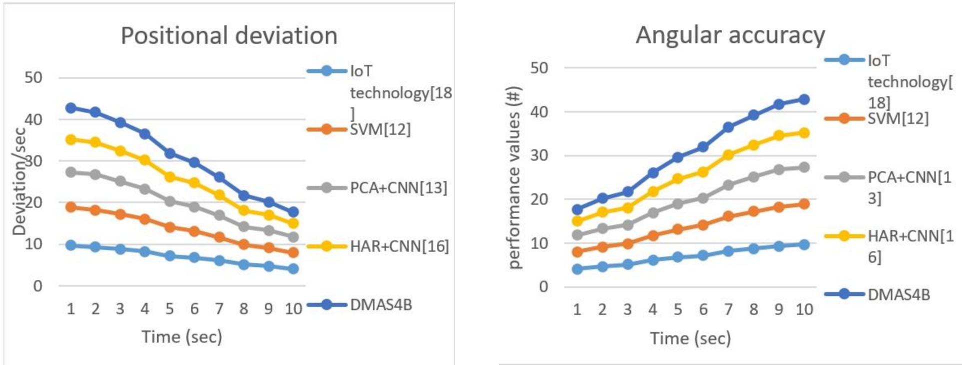
where, n represents the overall quantity of position samples; (x_{actual}, y_{actual}) are the current player positions; $(x_{recorded}, y_{recorded})$ are the positions of the players recorded by the system. Significant positional variation could impact a player's capacity to uphold precision of position on the court. It can result in errors in passing, accuracy while shooting, and placement on defence. For example, if the system incorrectly records an athlete's position, it could impact the player's choices based on the incorrect information [23,24].

Angular accuracy: Angular accuracy measures the level of accuracy in tracking rotational motion during certain basketball operations like shooting, dribbling, or defensive tactics. The metric could entail examining the difference between the real and documented angular positions. This can be expressed as an inclined deviation.

$$Angular\ deviation = \frac{1}{N}\sum_{i=1}^{N}\left|\theta_{actual,i} - \theta_{recorded,i}\right| \quad (13)$$

In the above Equation (13), N represents the overall quantity of angular position samples. Theta sub, a. c t u a. l, *i* denotes the true angular positioned by $\theta_{actual,i}$. The value $\theta_{recorded,i}$ represents the angular position recorded by the system. Accurate deviation data and comparisons with existing technologies would clarify the DMAS4B system's accuracy. Typical methods have positional variances of ± 5 cm to ± 10 cm, whereas the system reaches ± 1 cm, resulting in greater precision. This precise statistic shows how DMAS4B improves player movement tracking. This technology differs from others by offering angular precision of less than ± 1 degree, a significant improvement over the conventional ± 3 to ± 5 degree accuracy. Compared side by side, DMAS4B has better posture and motion tracking.

It would also be useful to compare the DMAS4B system to other sports training tools like motion capture systems and high-speed cameras. Showing how the DMAS4B performs under varying illumination or dynamic movements would help illustrate its usefulness. Real-world applications can highlight the practical benefits of enhanced angular accuracy and positional variation. The DMAS4B technology's precise input may help athletes improve their shooting positions. After these extensive numerical comparisons and assessments, the reader will better understand the DMAS4B system's capabilities and relative advantages. This improves the system's dependability and sports training value [25,26].



(a) Positional deviation **(b)** Angular accuracy

Figure 5. Tracking accuracy of athletes. **(a)** Positional deviation; **(b)** Angular accuracy.

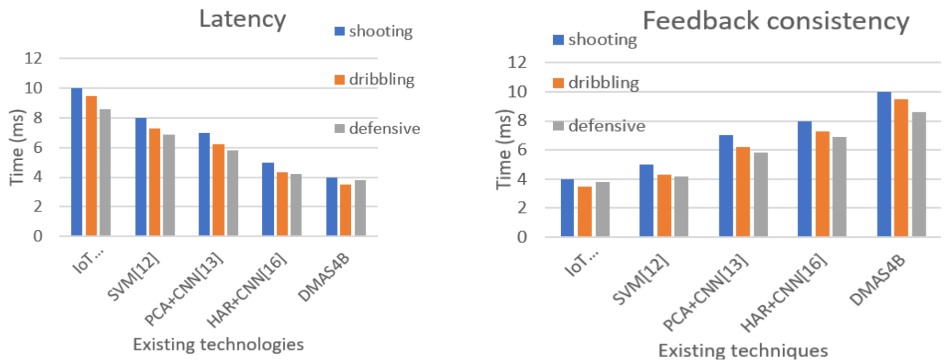
Precise tracking measurements from DMAS4B, such as positional difference, angular precision, and live coordination, have a notable effect on player effectiveness (a shown in **Figure 5**). Accurate feedback improves skills, helps make quick changes, and decreases the chances of getting hurt. This precision provides focused instruction, enhances player self-assurance, and facilitates customised skill enhancement. DMAS4B's accuracy improves player skill, promotes strategic practice, and boosts basketball performance through knowledgeable and prompt feedback.

4.1. Real-time monitoring performance

Latency analysis: This measurement evaluates the time lag between a player's movement (shooting or dribbling) and the system's reaction regarding their posture or technique. For example, when a player attempts or performs a particular move, the duration it takes over the system to give feedback on the method or posture employed during the action is measured. A decreased latency signifies a swifter system reaction, guaranteeing that the feedback is prompt and pertinent to the player's actions. Latency is the duration between when a player takes an action and when the system provides input. Equation (14) shows the mathematical estimation of the delay as follows:

$$Latency = t_{feedback} - t_{action} \tag{14}$$

where, $t_{feedback}$ is the period during which the system offers feedback. t_{action} is the moment when the player starts a certain action, such as shooting or dribbling. The **Figure 6** shows the real-time performance monitoring analysis. The discrepancy between these timestamps indicates the latency or system reaction time, which shows how promptly the system responds to the player's activity.



(a) Latency **(b)** Feedback consistency

Figure 6. Real-time performance monitoring. **(a)** Latency; **(b)** Feedback consistency.

Consistency of Feedback: This measure assesses the consistency and dependability of the system's prompt response in different training situations. The measurement assesses the system's ability to consistently give feedback on posture, method, or skill execution while the player performs various actions. A more minor standard deviation in feedback times as shown in Equation (15) indicates that the system consistently provides prompt responses across multiple training settings, ensuring that athletes obtain feedback consistently regardless of the action or scenario. Feedback consistency analyses the system's reaction timing variation across distinct occurrences. The standard deviation can indicate the variability of the response times.

$$Feedback\ consitency = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(t_{feedback,i} - \overline{t_{feedback,\imath}})^2} \qquad (15)$$

where, N represents the overall quantity of feedback instances. Feedback time for the *i*-th occurrence is $t_{feedback,i}$. The average response time $\overline{t_{feedback,\imath})}$ is the mean feedback time. A smaller standard deviation suggests more constant feedback timing, emphasising the system's reliability in giving immediate and uniform replies across various training settings.

4.2. Training impact

Skill improvement: Evaluating Skill Development: The suggested DMAS4B system may significantly improve basketball training abilities over time. Modern computer vision algorithms and Inertial Measurement Units (IMUs) that offer real-time feedback during play may assist athletes in remembering abilities. Players may improve their shooting, dribbling, and defensive alignments by regularly assessing and fixing biomechanical weaknesses. DMAS4B creates tailored training programmes based on each player's strengths and shortcomings to improve skill acquisition and encourage continual progress. DMAS4B can measure enhancements in basketball abilities such as shooting, dribbling, and defensive methods by comparing data before and after installation. Performance metrics like shooting precision, dribbling speed, location in defence, and other pertinent indicators are monitored. For example:

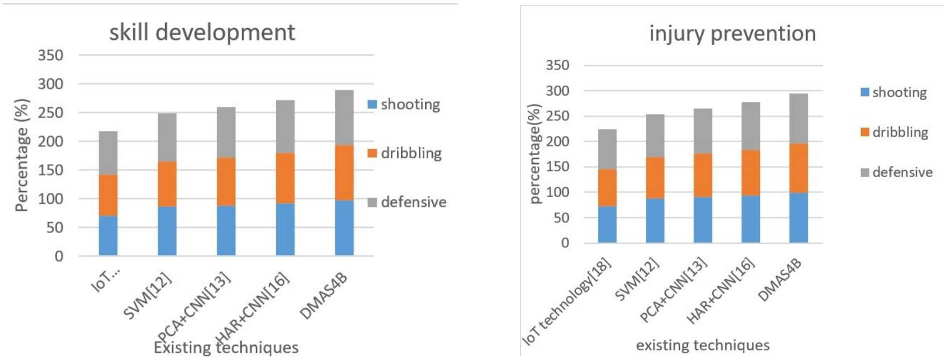
- Shooting Precision: Assess the proportion of shots that were successful by players before and after the system's installation.
- Dribbling action: Analyze the time players reach a given distance while dribbling

the ball before and after utilising the system.

- Defensive Positioning: Assess the efficiency of defensive stances or actions by examining the success rates of blocking or intercepting opponent manoeuvres.

Training adaptations based on data analysis: DMAS4B's feedback provides customised training sessions that focus on specific areas of improvement. Coaches and players utilise this data to focus on areas that require enhancement. For example:

- Customized Training Programs: Create tailored training plans according to each player's specific areas for improvement in shooting, dribbling, or defence.
- Skill Enhancement: Use accurate input to develop drills and routines that target specific weaknesses noticed in player performance. **Figure 7** shows the skill development analysis for basketball players' performance.



(a) skill development **(b)** injury prevention

Figure 7. Analysis of training impact. **(a)** skill development; **(b)** injury prevention.

Reducing the risk of injury: Analyzing Adjustments Driven by Feedback: Besides improving abilities, the DMAS4B system may prevent basketball training injuries. The technology identifies and reduces injury risk factors by recording athlete biomechanics and behaviours. Unlike conventional training approaches, quick feedback lets athletes fix technique issues before they damage themselves. Through motion pattern analysis, coaches may better prepare their athletes for injuries by identifying tendencies that may increase risk. As athletes improve, training becomes safer, healthier, and more effective for health and performance. DMAS4B's data helps identify inappropriate postures or movements that could cause injury. Analysing adjustments made in response to system feedback can help reduce these risks. For instance:

- Identification of Potentially Dangerous Movements: Examine situations in which players' body positions or actions could raise the risk of injury.
- Feedback-Driven Corrections: Assess modifications made by players to skills or movements following feedback received.
- Implementing Strategies to Prevent Injuries: Coaches and players use DMAS4B input to adopt methods to reduce the risk of injuries. This encompasses:
- Use feedback to correct posture, balance, or execution of actions likely to cause injuries.
- Education and Training Adjustments: Offer players information and adapt training methods to highlight safer tactics and movement patterns.

Using DMAS4B data to identify areas for improvement and injury risks, coaches and players can apply focused training programs and changes, improving abilities and potentially reducing the chances of injuries during basketball training and playtime.

4.3. Data analysis and visualisation quality

Clearness and Specificity of Visualized Data: Accuracy in the Analysis of Body Movements: DMAS4B produces visual data that captures detailed bodily movements. The system should offer clear, in-depth visuals that accurately analyse these movements. This encompasses.

- High-Definition Imaging: Ensuring sharp and detailed photos or videos of player actions, enabling accurate evaluation of body postures, angles, and motions.
- Visual Representation: Using graphs or diagrams to illustrate essential movement measurements (such as location and angles) in a way that is easy for coaches and players to comprehend.
- Zoom and Multiple Viewing Angles: Providing the option to zoom in or out and examine movements from different angles for a thorough evaluation.

Level of Comprehension: The visuals should be easy to understand and make sense to coaches and players. This includes:

- User-Friendly Interface: An interface built well, making navigating and understanding visual data simple without any complications.
- Emphasizing Important Measurements: Highlighting important movement patterns or deviations using visual cues such as colour coding and annotations to identify them quickly.

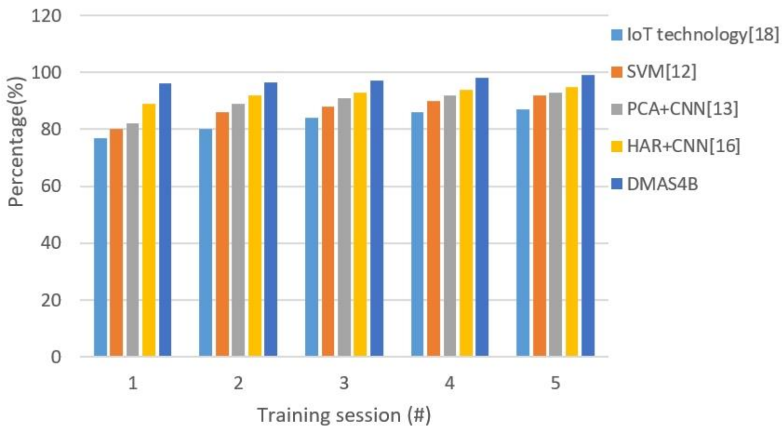


Figure 8. Effect of DMAS4B on basketball player movements during training sessions.

Thorough Examination using MotionPro+ Software: Analytical Features Depth: MotionPro+ should provide diverse analytical tools for comprehensively evaluating player motions and tactics. **Figure 8** shows the analysis of the effect of DMAS4B on basketball player movements during training sessions. This encompasses:

- Statistical Analysis: Offering statistical measures (mean, standard deviation) on motions, facilitating a numerical comprehension of player performance.
- Comparative Analysis: Enabling data comparison across various sessions or players to identify trends and benchmark performance.

- Segmentation and Tagging: Capability to divide particular movements or acts into segments and label them for concentrated examination and referencing.

Analytical Range: MotionPro+ should thoroughly address different areas of player movement analysis. This encompasses:

- Multiple Skill Analysis: Allowing the evaluation of various skills (shooting, dribbling, defence) simultaneously throughout a session to provide a comprehensive assessment.
- Live Analysis: Offering immediate insights during training sessions for prompt feedback and adjustment.

A reliable DMAS4B system combined with robust MotionPro+ software should provide clear, detailed, and simply understandable visualisations while offering a variety of analytical tools to comprehensively evaluate and comprehend player motions in basketball training. Versatile sensor integration lets the DMAS4B system adapt to various sports. This allows activity-specific biomechanics-based IMU and conjugated polymer composite calibration and installation. Due to this flexibility, gymnastics, soccer, and tennis motions may be reliably identified. Computer vision algorithms can assess runner and golfer gaits. Since movement analysis and performance improvement are universal, coaches may utilise DMAS4B data to improve training regimens for players in many sports. Finally, adding athletic gear to DMAS4B may enhance it. Additional sensors or modules that give sports-specific data might boost the platform's value. The DMAS4B method currently helps basketball players of all levels and is relevant to many sports, improving athletic performance and injury avoidance.

5. Discussion

The DMAS4B method has worked with basketball players of different abilities and skill levels, proving its versatility. The system's basic training activities and feedback may assist novices in shooting, passing, and dribbling. This personalised strategy gives newcomers the instruction they need to build a solid gaming foundation. The most complicated analytic and advanced training modules of the DMAS4B system are for intermediate and advanced players to increase performance and concentrate on game details.

The system may be adjusted for casual to extremely competitive leagues. Coaches may utilise DMAS4B data to construct tailored training regimens for their athletes to prepare for competition. Players may understand their strengths and development areas using thorough statistics. They may practice for competitive difficulties and develop. The DMAS4B technology enables coaches to create tailored training programmes for basketball players of different skill levels and game types, improving performance.

6. Conclusion

Using conjugated materials is one innovative endeavour to transform sports performance and injury prevention in basketball training. DMAS4B, a cutting-edge wearable system, combines advanced technology, including computer vision algorithms, Inertial Measurement Units (IMUs), and flexible polymers incorporated in sportswear. This integration allows for the live tracking and examination of basketball player movements during training sessions. The system's careful positioning of materials ensures lightweight, durable, and flexible gear, allowing for accurate movement tracking that meets training needs, ultimately improving performance and refining technique. The design of DMAS4B focuses on gathering detailed body movement data, giving importance to essential basketball abilities such as shooting accuracy, dribbling methods, and defensive positions. The data is sent wirelessly to the MotionPro+ Basketball Analytics Software, a dedicated platform for in-depth analysis and visualization of player movements. The cooperative aspect of IMUs, versatile polymers, and computer vision algorithms highlights the system's ability to precisely capture and analyse basketball movements. The implementation connects traditional training methods with advanced technology, providing athletes and coaches with immediate, detailed feedback on posture, balance, and skill proficiency. Future possibilities for DMAS4B include ongoing improvements to enhance accuracy and functionality, potential use in various sports, extensive research to link data with injury prevention strategies, improvements to the user interface for more straightforward interpretation, and long-term studies to assess its long-lasting effects on skill improvement and injury prevention. This technology combines new technologies to enhance sports training methods, offering the possibility for increased performance and injury prevention not only in basketball but also in other sports. The experimental results show a deviation of 2.1 sec performance of 2.1 sec, latency of 4 ms, feedback consistency of 10 ms, skill development of 96%, injury prevention ratio of 98%, and training session of 99% compared to other methods.

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