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Molecular & Cellular Biomechanics 2025, 22(3), 1279.
https://doi.org/10.62617/mcb1279

Article

Detection and biomechanical analysis of human posture embedded electronic system based on D-H matrix method

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CITATION

Huang Y. Detection and biomechanical analysis of human posture embedded electronic system based on D-H matrix method. Molecular & Cellular Biomechanics. 2025; 22(3): 1279. https://doi.org/10.62617/mcb1279

ARTICLE INFO

Received: 31 December 2024
Accepted: 23 January 2025
Available online: 19 February 2025

Abstract: Background: This study aims to model the kinematics of human joints using the Denavit-Hartenberg matrix method (hereinafter referred to as D-H matrix method) and combine biomechanical analysis for posture evaluation, thereby providing a more accurate and efficient detection solution. It ensures the implementation of complex calculations under low-power conditions and has broad application prospects in fields such as rehabilitation medicine, sports analysis, and virtual reality. **Objective:** The aim of this study is to design a sensor fusion-based embedded electronic system by integrating nine-axis sensors such as accelerometers, gyroscopes, and magnetometers. This system combines the D-H matrix method and forward kinematics for human posture detection and biomechanical analysis, to improve the system's detection accuracy and response speed. **Methods:** Traditional forward kinematics and the D-H matrix method are used for kinematic modeling to enhance the accuracy and efficiency of posture calculation. **Innovation:** The D-H matrix method, a classical analysis technique in robotics typically used for kinematic analysis of robotic arms, is successfully applied in this study to human posture detection, breaking through traditional posture analysis methods. By utilizing the D-H matrix method to model the movement relationships between human joints, this study provides a more precise mathematical model for posture detection. By combining embedded electronic systems with biomechanical analysis to evaluate human posture, and introducing real-time monitoring of biomechanical loads from a biomechanical perspective, this study ensures that real-time human posture detection is not only efficient but also capable of performing complex calculations under low power conditions. **Results:** To further improve the accuracy of the sensors, this study analyzed the error characteristics of the inertial sensors and applied preprocessing algorithms to correct the errors in the signals from the magnetometer, accelerometer, and gyroscope. Combined with a high-pass and low-pass complementary filter fusion algorithm, the experiment showed that this algorithm successfully resolved the random drift and cumulative errors in the attitude angles calculated. The posture calculation system using the D-H matrix method outperforms the traditional forward kinematics method in terms of response time and root mean square error (hereinafter referred to as MSE). For instance, the response time for the right upper arm is reduced by 74.67% compared to traditional methods, while the MSE remains within a reasonable range.

Keywords: sensor; embedded electronic system; human posture detection; traditional forward kinematics; D-H matrix method

1. Introduction

Human body posture detection is an important topic in the fields of computer vision and biomedical engineering [1]. With the continuous advancement of modern intelligent technology, how to enable machines to more comprehensively understand and analyze human posture and movements has become a key issue [2]. Traditional posture detection methods mostly rely on visual image data, and with technologies such as deep learning and Convolutional Neural Network (hereinafter referred to as

CNN), significant achievements have been made in various fields, including healthcare, sports, robot interaction, and autonomous driving. However, with the widespread use of embedded devices and mobile platforms, real-time and efficient human body posture detection research has become increasingly important, especially for how to efficiently complete large-scale computational tasks in resource-constrained embedded platforms [3–5]. Against this background, sensor fusion-based embedded electronic systems have become a research hotspot.

This paper designs an embedded electronic system by combining Micro-Electro-Mechanical Systems sensors (hereinafter referred to as MEMS sensors) such as 3-axis accelerometers [6], gyroscopes, and magnetometers, which can capture human motion states and posture changes [7]. This system can effectively compensate for the lack or limitation of visual image information in certain scenarios. Through sensor data fusion and posture estimation algorithms, this paper achieves real-time monitoring of human posture, which can be applied to sports analysis, fall detection, health management, and various biomedical applications [8–10].

In recent years, research in the field of human posture detection has shown a trend of diversification and depth. From the early DeepPose model to later models like OpenPose and RMPE [11], the progress of deep learning and computer vision has greatly improved the accuracy of posture detection. In particular, enhancing the accuracy of human posture recognition through multi-model fusion and spatial feature extraction in complex scenarios has become a key research direction [12]. Meanwhile, with the development of hardware technology, more and more embedded platforms are being introduced into human posture detection systems, such as robots with dedicated AI chips and autonomous driving systems [13]. These platforms require optimized computational efficiency to handle high concurrency and large computational loads in posture detection tasks. Additionally, the application of sensor fusion technology in biomedical engineering has also received widespread attention. MEMS sensors have become the primary tool for modern human posture monitoring, and the small size, low power consumption, and low cost of MEMS make them suitable for use in embedded devices [14–16]. Sensor data fusion can effectively improve detection accuracy and reduce errors that may arise from using individual sensors. By combining accelerometers and gyroscopes, we can calculate human acceleration and angular velocity, which can further estimate posture changes. The magnetometer can provide a more accurate heading angle, helping to improve the overall accuracy of posture estimation and overcoming errors in certain motion states, further enhancing the reliability of posture detection [17].

Thus, the application of sensor fusion-based embedded electronic systems in human posture detection and biomechanical analysis has significant academic value and practical significance. The research presented in this paper provides an efficient real-time posture detection solution for embedded platforms, effectively overcoming the limitations of traditional visual detection, such as high hardware performance requirements and computational complexity, making it particularly suitable for resource-limited mobile platforms and smart devices. At the same time, sensor fusion technology maximizes the advantages of different sensors, improving detection accuracy and reducing the error influence of individual sensors, making human posture detection more precise and reliable. In summary, the application of sensor fusion-based embedded electronic systems in human posture detection not only promotes technological progress in the field of biomedical engineering but also provides feasible technical paths for various practical applications, holding significant academic and social value [18]. Therefore, the goal of this study is to design a sensor fusion-based embedded electronic system using the D-H matrix method, combining MEMS sensors such as a three-axis accelerometer, gyroscope, and magnetometer to achieve high-precision and reliable human posture detection. The focus of this research is on applying the D-H matrix method to optimize the posture estimation process, improve response time, and reduce errors, providing a practical real-time solution that can be widely applied in fields such as motion analysis, fall detection, health management, and biomedical engineering.

2. Research methods

2.1. Human skeletal model method

The construction of a human skeletal model is fundamental in the fields of biomechanics, biomedical engineering, and human posture detection. It aims to accurately simulate human motion and posture through mathematical and computational models. The human skeletal system consists of multiple joints and bones, with each joint having a different degree of freedom, which results in the complex nonlinear characteristics of human movement [19]. To simplify this complex system, human skeletal models typically use principles from geometry and rigid body mechanics.

Firstly, the human skeletal system contains approximately 206 bones, which form a relatively rigid structure through joints. The ends of each bone are connected by joints, and the degrees of freedom (hereinafter referred to as DOF) of the joints determine their range and direction of movement. The DOF vary depending on the structure of the joint. For example, the shoulder joint (ball-and-socket joint) and hip joint (ball-and-socket joint) typically have three DOF, allowing for multi-directional movements such as flexion, extension, internal and external rotation, and abduction and adduction. In contrast, the finger joints have only one degree of freedom, permitting movement in a single direction such as flexion and extension [20].

To build the human skeletal model, a simplified approach is commonly used, where bones are treated as rigid bodies. This assumption means that the bones do not deform during motion, allowing their movement to be described by rigid body kinematics. This simplification significantly reduces the complexity of the model, making it possible to model and analyze human movement.

When constructing the human skeletal model, it is also essential to consider the three basic planes of human motion: the coronal plane, sagittal plane, and horizontal plane. The DOF of each joint are typically defined by these three perpendicular planes, describing motion along them. For example, flexion and extension occur along the coronal axis, abduction and adduction along the sagittal axis, and internal and external rotation along the vertical axis [21].

Moreover, the human skeletal model does not only include bones and joints but also needs to account for the role of ligaments. Ligaments provide stability to joints and restrict excessive movement. However, due to the complexity and dynamic nature of ligaments, their modeling often relies on empirical data or simplified assumptions [22].

Overall, the construction method of the human skeletal model primarily relies on treating bones as rigid bodies and simplifying the DOF and range of motion of the joints. Through the establishment of mathematical models and computer algorithms, human motion can be described. This approach not only provides theoretical support in biomechanics research but also lays the foundation for practical applications in fields such as medicine, sports science, and robotics. A diagram of the human skeletal structure model is shown in **Figure 1**.

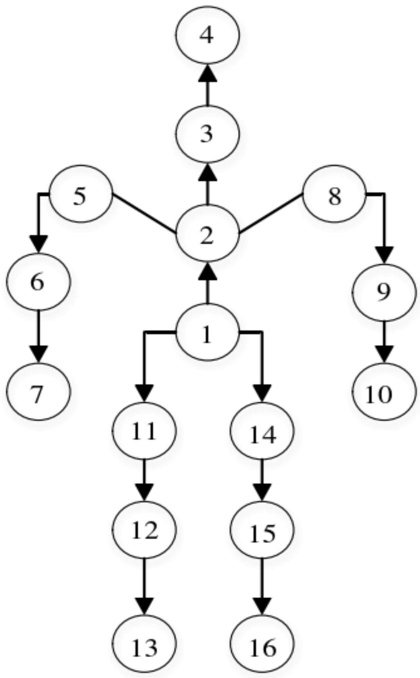

Figure 1. Human skeletal structure model diagram.

Among them, the Body Part is shown as the **Table 1**.

Table 1. The Body Part.

Number	Body Part	Number	Body Part
1	Waist Joint	9	Right Elbow Joint
2	Chest Joint	10	Right Hand
3	Neck	11	Left Hip Joint
4	Head	12	Left Knee Joint
5	Left Shoulder Joint	13	Left Foot
6	Left Elbow Joint	14	Right Hip Joint
7	Left Hand	15	Right Knee Joint
8	Right Shoulder Joint	16	Right Foot

2.2. Constraints of human motion model

The constraints of the human motion model typically include joint angle range limits, DOF constraints, and inter-joint constraints. By calculating the angles of the joints using the spatial vector method and setting appropriate angle range limits, the motion of the human skeleton can be effectively simulated and described. For complex multi-degree-of-freedom joints, it is also necessary to consider motion constraints within multiple planes to ensure the accuracy and validity of the model [22].

In the human motion model, the motion of joints is constrained by their DOF and angle limits. Different types of joints have different DOF, and the range of motion for each joint also varies. To describe these constraints, the spatial vector method is commonly used to calculate the joint angle ranges. The specific constraint formulas are based on vector operations, and by restricting the rotational or angular movement of the joints, the range of motion for each joint can be defined.

For different joint locations, the DOF and angle limits vary. Ignoring Gaussian white noise, the joint angle range can be calculated using the spatial vector method as shown in the following formula:

$$\beta_1 \leq arccos \frac{X_{tu}^x \bullet X_{td}^x}{|X_{tu}^x \bullet X_{td}^x|} \leq \beta_2.$$

Among them, X_{tu}^x and X_{td}^x represent the x-axis vectors of the upper arm and lower arm at time *t* in the skeletal coordinate system.

2.3. Joint degree of freedom constraints

The degree of freedom of each joint can be limited by setting the maximum and minimum values of the angle. For example, for single-axis rotational joints (such as the elbow joint, knee joint, etc.), the degree of freedom can be constrained by setting the rotation angle range within a plane [23]. Assuming the joint's rotational angle is θ, its degree of freedom constraint can be expressed in the following form:

$$\beta_{min} < \beta < \beta_{max},$$

where β_{min} and β_{max} represent the minimum and maximum rotational angles of the joint.

For complex multi-degree-of-freedom joints (such as the shoulder joint, hip joint), more complex constraint conditions are required. For example, the rotation of the shoulder joint is not limited to a rotation within a single plane but also includes internal and external rotation, as well as flexion and extension [24]. Therefore, multiple degree-of-freedom constraints need to be defined separately:

Internal and external rotation: Rotation around the vertical axis, typically constrained within the range of $[\beta_{min}, \beta_{max}]$.

Flexion and extension: Rotation around the coronal axis, typically constrained within the range of $[\beta_{min}, \beta_{max}]$.

Abduction and adduction: Rotation around the sagittal axis, typically constrained within the range of $[\beta_{min}, \beta_{max}]$.

Table 2 summarizes the range of motion for the human joints in terms of flexion and extension around the coronal axis, abduction and adduction around the sagittal axis, and internal and external rotation around the vertical axis.

Table 2. Range of motion of human joints.

Joint	Flexion (−) and Extension (+)	Abduction (−) and Adduction (+)	Internal Rotation (−) and External Rotation (+)
Neck	[−45°~45°]	[−45°~45°]	[−75°~75°]
Shoulder Joint	[−30°~90°]	[−45°~90°]	[−80°~30°]
Elbow Joint	0	[0°~140°]	[−90°~90°]
Waist	[−30°~30°]	[−30°~90°]	[−30°~30°]
Hip Joint	[−20°~30°]	[−40°~145°]	[−45°~45°]
Knee Joint	0	[−145°~0°]	[−10°~20°]

2.4. Traditional forward kinematics model

The traditional forward kinematics model primarily involves the calculation of relative motion between joints, especially how to use forward kinematics to describe the effect of the angular changes in each joint of the arm on the end effector (such as hand position and orientation). To simplify the calculation and reduce the system's computational load, this paper simplifies the human body into a model with 11 joints and 25 DOF, including the shoulder joint, elbow joint, and wrist joint, with a primary focus on the motion of the arm within a plane [25].

The key part of the human arm model is the motion of the shoulder, elbow, and wrist joints. The motion of each joint is determined by the relative rotation angle between it and the previous joint. By defining these angles, we can use forward kinematics to solve for the position and orientation of the end effector. The shoulder joint is a three-degree-of-freedom ball-and-socket joint, with DOF for flexion/extension, abduction/adduction, and internal/external rotation [26]. Each degree of freedom can be described by an angle, usually denoted as $\theta 1$. The elbow joint is a single-axis hinge joint with only flexion/extension, typically represented by $\theta 2$. The wrist joint consists of two DOF, mainly for wrist rotation and flexion/extension, with the angle denoted as $\theta 3$.

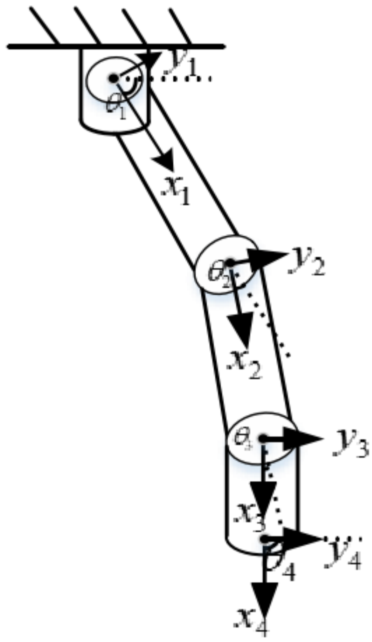

Figure 2. Traditional forward kinematics model.

Forward kinematics primarily involves calculating the position and orientation of the end effector from known joint angles. By solving forward kinematics for the angles of each joint and their effect on the end effector, we can effectively simulate arm movement. Accurate joint angle calculations and reasonable angle constraints provide support for human posture estimation in both simulations and real-world applications. This model reduces the computational load while ensuring sufficient accuracy, making it suitable for embedded systems or other scenarios requiring real-time feedback. The traditional forward kinematics model is shown in **Figure 2**.

2.5. D-H matrix method

The D-H matrix method (Denavit-Hartenberg method) is a technique used to describe the kinematics of multi-degree-of-freedom robotic arms or multi-joint robots. It simplifies the description of the geometric relationships between adjacent joints and links by defining a set of standardized coordinate frames, and then uses homogeneous transformation matrices to solve for the position and orientation (pose) of the end effector. The D-H method is widely used in robotics and biomechanics for joint chain kinematics analysis [27].

The D-H matrix method describes the relative motion between each joint by defining four parameters that determine the transformation relationship between adjacent coordinate frames. These four parameters are:

θ: The rotation angle of the joint (rotation around the z-axis of the current joint).

d: The offset of the joint (translation along the z-axis of the current joint).

a: The length of the link (translation along the x-axis of the current joint).

α: The twist angle of the link (rotation along the x-axis of the current joint).

For each pair of adjacent coordinate frames, a homogeneous transformation matrix (4 × 4 matrix) can be used to represent the relationship between them. This transformation matrix is composed of the four D-H parameters and is expressed as follows:

$$A_i^{i-1} = \begin{bmatrix} cos(\theta_i) & -sin(\theta_i)\,cos(\alpha_i) & sin(\theta_i)\,sin(\alpha_i) & \alpha_i\,cos(\theta_i) \\ sin(\theta_i) & cos(\theta_i)\,cos(\alpha_i) & -cos(\theta_i)\,sin(\alpha_i) & \alpha_i\,sin(\theta_i) \\ 0 & sin(\alpha_i) & cos(\alpha_i) & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

where θ_i, d_i, a_i, and α_i are the D-H parameters, representing the rotation angle, displacement, link length, and twist angle of the i-th joint, respectively.

The first column represents the transformation in the x-axis direction.

The second column represents the transformation in the y-axis direction.

The third column represents the transformation in the z-axis direction.

The fourth column represents the translation transformation.

The D-H matrix method provides a powerful mathematical tool for the kinematic analysis of multi-degree-of-freedom robotic arms and human skeletal models. Through standardized coordinate system definitions and simplified transformation matrix expressions, it can effectively describe the relative motion between joints and provide precise solutions for calculating the pose (position and orientation) of the end effector. In practical applications, the D-H matrix method is widely used in fields such as robot control, animation production, and virtual reality.

2.6. Combination of D-H matrix method and forward kinematics

The combination of the D-H matrix method and forward kinematics still holds a certain degree of innovation. In this paper, the introduction of the D-H matrix method is not merely a simple repetition of existing methods. By optimizing the D-H matrix method, it allows for more accurate handling of multi-joint human posture estimation, especially in dynamic situations, providing better adaptability and precision. This can address the limitations of traditional forward kinematics methods in real-time and complex motion estimation. The D-H matrix method optimizes the relative motion relationship between joints by modeling each joint independently, reducing error transmission and improving precision and stability. Compared to traditional methods, the D-H matrix method can effectively reduce redundant calculations between joints, enhancing the overall system's response speed.

The advantage of the D-H matrix method lies in its modularity and scalability, making posture estimation in multi-sensor fusion applications more manageable. This method can not only be applied to simple 2D posture estimation but can also be expanded to more complex 3D kinematic analysis. Compared to traditional kinematic methods, the D-H matrix method provides stronger alignment and compensation capabilities between different sensor data. This is particularly important in multi-sensor environments (e.g., fusion of accelerometers, gyroscopes, and magnetometers), as it reduces errors and deviations between sensors, thereby improving the overall reliability and accuracy of the system.

The combination of the D-H matrix method and forward kinematics can effectively overcome the limitations of traditional forward kinematics methods in complex posture estimation, particularly in terms of response time and real-time performance. Through optimization of the D-H matrix method, it provides faster feedback in dynamic environments, especially in scenarios where motion changes are large or rapid, allowing for more precise posture tracking.

2.7. Precision measurement method

In a human posture detection system, precision measurement is an important aspect of evaluating system performance, especially in multi-node precision experiments. By accurately measuring joint movements, the system's accuracy can be effectively verified. This section uses a two-node precision experiment to test the system. The D-H matrix method is used to calculate the relative motion relationships between joint chains and adjacent joint chains, further evaluating the precision of sensor nodes in human posture measurement [28].

The most commonly used precision evaluation method is the Root Mean Square Error (RMSE), which effectively measures the deviation between the measured values and the theoretical values. The RMSE calculation formula is as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - X_i')^2},$$

where:

X_i represents the sensor measurement (actual measured value).

X_i' represents the theoretical value (calculated through the D-H matrix method or other theoretical methods).

n represents the total number of measurements.

To evaluate the performance of a classification model, metrics such as accuracy, precision, recall, and F1 can be used. The formulas are as follows:

Accuracy: Accuracy=$\frac{\mathrm{TN}+\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}+\mathrm{TN}+\mathrm{FP}}$;

Precision: Precision=$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$;

Recall: Recall=$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$;

F1: $\mathrm{F1}=2\times\frac{\mathrm{Precision}\times\mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}}$;

where TP is true positive, TN is true negative, FN is false negative, and FP is false positive.

3. Research results

3.1. Sensor module design

The sensor module is the core measurement unit in the human posture detection system, primarily responsible for collecting acceleration, angular velocity, and magnetic field strength values from various detection nodes of the human body. These analog signals are then converted into digital data for the microcontroller unit (hereinafter referred to as MCU) to perform posture computation. The sensor module typically includes three basic sensors: accelerometers, gyroscopes, and magnetometers. These sensors work together to provide comprehensive motion information, enabling the accurate calculation of the posture and motion status of each joint in the human body.

There are various nine-axis MEMS inertial sensors available in the market. Common models includehereinafter MEMS 9-Axis Motion Sensor (hereinafter referred to as BMX055), LIS3MDL, LSM6DS0—9-Axis MEMS Inertial Measurement Unit (hereinafter referred to as LSM9DS0), and InvenSense 9-Axis MotionTracking™ Device(hereinafter referred to as MPU9250). These sensors are widely used in consumer electronics, smart wearables, and robotics. The BMX055 offers high precision and low power consumption, making it suitable for low-power embedded systems and supporting gyroscope measurements up to 2000 °/s. The LSM9DS0 has strong anti-interference capability and a wide operating temperature range, making it suitable for motion capture in complex environments. The MPU9250 has strong overall performance, high integration, and supports high measurement accuracy, making it suitable for applications that require high precision and low latency. These sensor modules are connected to the MCU via I2C or Serial Peripheral Interface (hereinafter referred to as SPI) interfaces to transmit sensor data and perform further processing.

Power management of the inertial sensor module is an important aspect of the design, especially in portable and embedded applications. Selecting low-power sensors and designing efficient system work cycles are effective methods for optimizing power consumption. The nine-axis inertial sensor chip used in this study is shown in **Table 3**.

Table 3. Comparison of common nine-axis inertial sensor chips.

Sensor	Accelerometer		Gyroscope		Magnetometer	
	Sensitivity (mg/LSB)	**Range (g)**	**Sensitivity (mdps/LSB)**	**Range (°/s)**	**Sensitivity (μT/LSB)**	**Range (μT)**
BMX055	0.977	±2–±16	3.811	±125–±2000	0.3	±2500
LSM9DSO	0.061	±2–±16	8.750	±250–±2000	0.8	±1200
MPU9250	0.061	±2–±16	7.634	±250–±2000	0.6	±4800

3.2. Sensor calibration

In the process of using motion sensors, the initial calibration and accuracy verification of the sensors are key steps to ensure data reliability. First, the sensors are fixed to the joints of the human body using self-adhesive elastic bands. However, due to the misalignment between the sensor axis and the joint axis, it becomes difficult to accurately calculate the posture angles between the skeletal coordinate system and the world coordinate system. Therefore, after the sensor is installed, initial calibration must be performed to reduce installation errors and alignment errors between sensors. The calibration process is completed by having the arm naturally hang down to the ground and keeping the body still, ensuring that the initial sensor data is accurate. During this process, the accelerometer and magnetometer data measurements are used to complete the calibration of the static standing posture, ensuring that the data output from the sensors matches the actual posture of the body. The movement of the human body and the virtual model during the elbow joint rotation process is shown in **Figure 3**.

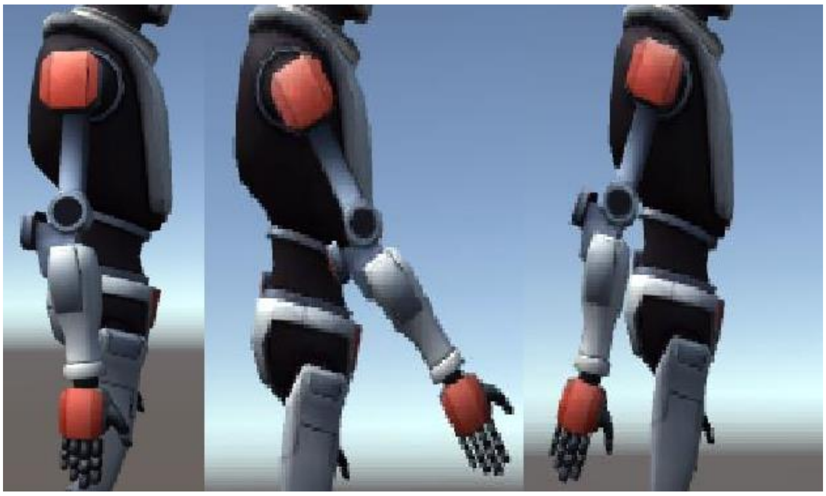

Figure 3. Shoulder joint forward and backward movement.

After sensor calibration is completed, a single-node accuracy experiment is conducted to verify the sensor's accuracy. Sensor node 1 is selected to be bound to the right upper arm of the body, connected to the power supply and 2.4G wireless module, simulating the shoulder joint movement. Then, the shoulder joint movement is simulated through the upper computer, and the sensor data is observed and saved. The data is analyzed using MATLAB, and the dynamic changes of the posture angles are observed. The specific experiment includes testing the forward and backward movement of the shoulder joint, where the arm is rotated by a certain angle along the sagittal axis and then returns to the initial position, followed by reverse rotation to restore the original position. This dynamic motion test helps detect the sensor's performance in actual movement and further verifies its accuracy. Accelerometer X-Axis Output Before and After Calibration is shown in **Figure 4**.

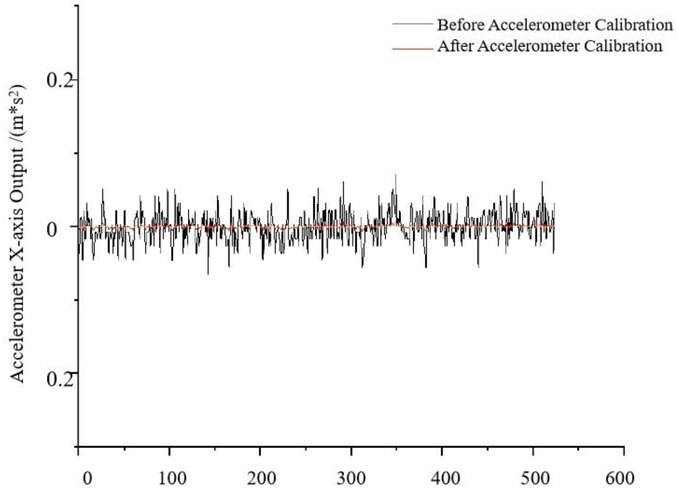

Figure 4. Accelerometer x-axis output before and after calibration.

3.3. Testing of the human posture detection platform

Six types of continuous behavioral postures were collected to test the posture detection platform. The acceleration data of the collected postures are shown in **Figure 5**.

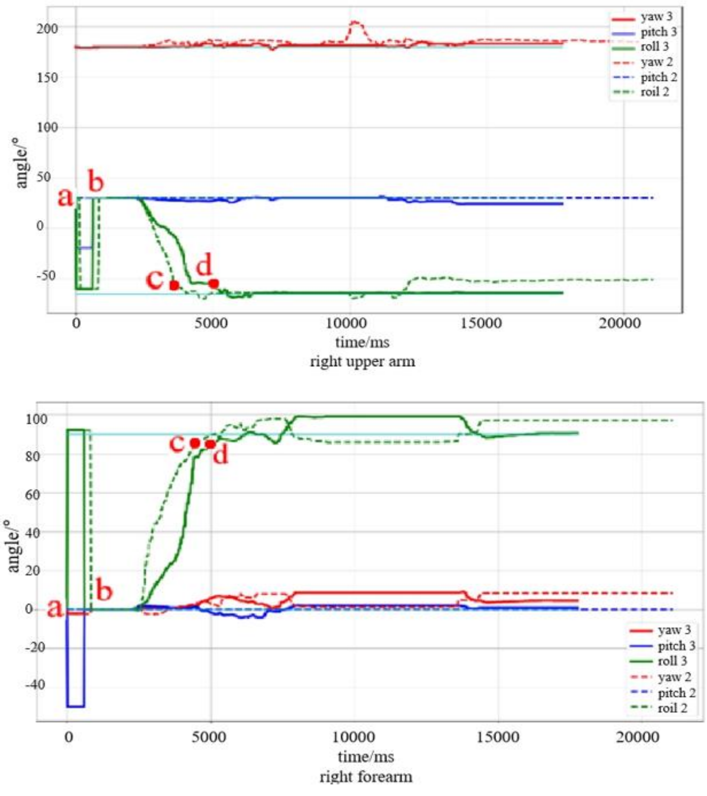

Figure 5. Approximation curves of D-H method and forward kinematics method.

The dashed line represents the D-H matrix method, and the solid line represents the traditional forward kinematics method. The dashed line in the image represents the value changes obtained by the D-H matrix method, while the solid line represents the values from forward kinematics, and the horizontal line represents the actual value corresponding to the model when the arm is lifted to 90°. Point A corresponds to the value of the original sensor, at which the baseline value is cleared. Point B represents the value after transformation into the human body coordinate system. Due to certain errors in the binding of the body with forward kinematics and the D-H matrix method, fluctuations in values occur. The points C and D, with errors approximating 5% to the actual value, are used to obtain the time values for points C and D.

3.4. Human posture detection data

This section presents the response time and MSE (Mean Squared Error) of the detection data, as shown in **Table 4**.

Table 4. Data comparison between D-H matrix method and traditional forward kinematics method.

	D-H Matrix Method		**Forward Kinematics**		**Response Time Ratio**	**MSE Ratio**
	Response Time (ms)	MSE	Response Time (ms)	MSE		
Right Upper Arm	3989.5	14.0693	5342.76	13.6578	74.67%	103.01%
Right Forearm	4560.15	15.4732	5231.58	17.6358	87.17%	87.74%
Left Upper Arm	1499.85	7.6356	2521.44	9.3228	59.48%	81.90%
Left Forearm	2009.9	10.9686	2633.64	11.4546	76.32%	95.76%

According to the data in **Table 4**, the D-H matrix method shows a slight improvement in Mean Squared Error (MSE) compared to the forward kinematics method, particularly in terms of response time, which has significantly improved. For example, the response time of the right upper arm was reduced by 74.67% compared to the forward kinematics method. Overall, the D-H matrix method improved the response time by approximately 20%, and the MSE remained within a reasonable range in most test cases, indicating its reliability in terms of accuracy. Therefore, the D-H matrix method not only enhances the response speed of human posture detection but also maintains good detection accuracy, making it suitable for various human posture detection tasks.

This paper evaluates the pose recognition model, as shown in **Table 5**.

Table 5. Evaluation results of the pose recognition model.

	Recall	**Precision**	**F1**	**Accuracy**
Right Upper Arm	0.922	0.938	3.219	91.405
Right Forearm	0.964	0.934	3.417	
Left Upper Arm	0.935	0.925	3.220	
Left Forearm	0.891	0.902	2.881	

According to **Table 5**, the right upper arm demonstrates high performance. The posture recognition for the right upper arm is excellent, with both recall and precision at high levels, indicating that the model is capable of effectively recognizing and accurately classifying most postures, while also avoiding misidentification. The evaluation of the right forearm is also outstanding. The high recall means the model can recognize more correct postures, and the relatively high precision indicates that the recognition results are highly accurate. The performance for the left upper arm is somewhat weaker. Compared to the right upper arm and right forearm, the left upper arm shows a slight decline, especially in the F1 score, suggesting that the model may have some bias in recognizing the posture of the left upper arm. The evaluation results for the left forearm are relatively lower. Although the recall and precision are still quite close, the F1 score is lower, indicating that the model may have some error in recognizing the posture of the left forearm, with the recognition accuracy and stability being weaker.

4. Discussion

4.1. Sensor module performance analysis

In this study, the sensor module design chose nine-axis inertial sensor chips such as BMX055, LSM9DS0, and MPU9250. The experimental results show that these sensors have good sensitivity and range, effectively capturing the motion information of various joints in the human body. However, the sensor selection still has certain limitations, especially in high-dynamic environments, where sensor data may be affected by noise and interference. For the accelerometer, BMX055 has the highest sensitivity (0.977 mg/LSB), but its error is more significant when there are large changes in acceleration. On the other hand, the MPU9250 strikes a good balance between precision and power consumption, making it suitable for applications that require high precision and low latency. Therefore, the selection of sensors should be weighed based on the specific application scenario and requirements. While the sensors can provide high-precision measurements, ensuring data reliability in complex environments remains a problem to be addressed in practical applications. The current design mainly relies on raw sensor data and basic algorithm processing, but in some special environments, sensor errors may affect the overall detection results.

4.2. Comparison and optimization of pose detection algorithms

In the design of the pose detection system, the D-H matrix method and traditional forward kinematics method were used for pose computation. By comparing the experimental data in **Table 4**, the results show that the D-H matrix method outperforms the traditional forward kinematics method in terms of response time and mean square error (MSE). Specifically, the response time for the right upper arm is 3989.5 ms, which is about 74.67% faster than the traditional method's 5342.76 ms. The MSE also shows a small difference, with the D-H matrix method being 14.0693, which is almost identical to the traditional method's 13.6578. This advantage is mainly due to the D-H matrix method's ability to simplify the complex mathematical derivation process and optimize the coordinate transformation formula, making the pose computation more efficient and accurate. The traditional forward kinematics method has some limitations in computational complexity and accuracy, especially in multi-joint and complex motion scenarios, where larger errors and response time delays are more likely to occur. Although the D-H matrix method shows superior performance in several aspects compared to the traditional method, there is still room for optimization. For example, in high-frequency movements (such as rapid rotations and jumps), the D-H matrix method still experiences calculation delays and needs further optimization in data acquisition and transmission processes to reduce errors caused by sensor data delays.

4.3. Data processing and system optimization

The experimental results show that the system has a significant advantage in response time and MSE, but different performance results are reflected in the test data from different body parts. For example, there is a large difference in the detection response time between the left lower arm and the right upper arm. The response time for the left lower arm is 2009.9 ms, while the right upper arm is 3989.5 ms. This may be related to factors such as the movement characteristics of the joints, sensor positioning, and data processing workflow. From the MSE perspective, the MSE values for the right upper arm and left lower arm are 14.0693 and 10.9686, respectively. Although there is a large difference between the two, the overall error is controlled within a reasonable range. This suggests that there are certain discrepancies in the pose computation accuracy for different body parts, and future improvements could involve personalized calibration or algorithm optimization for different joint movements to further enhance overall accuracy. In terms of data transmission and coordinate transformation, the system has already achieved an efficient design, ensuring rapid information transfer and real-time feedback. Through reasonable collaboration between hardware and software design, the system can ensure data accuracy and stability. However, real-time data processing remains a challenge, especially in high-dynamic movements. Further optimization of algorithms is required to minimize sensor data loss and processing delays.

4.4. Sensor fusion-based human posture detection application

The Perception Neuron™ Studio system, produced by Beijing Noitom Technology, utilizes high-precision motion capture capabilities to track patients' body posture, movement trajectories, and joint angles in real-time, with a particular focus on finger gestures and large dynamic movements. For example, during post-surgical rehabilitation training, the movements of a patient's arms, fingers, and other parts of the body can be comprehensively monitored using this system. The system's data processing frame rate reaches 800 Hz, providing sufficient accuracy and response speed, ensuring that each movement is monitored with high time resolution, thus better supporting real-time adjustments to the treatment plan.

In practical applications, Perception Neuron™ Studio has been used in the rehabilitation training of professional athletes. For instance, a patient who underwent knee replacement surgery wore the motion capture gloves and sensors during rehabilitation. By monitoring the patient's movements during physical therapy in real-time, doctors can evaluate the range of motion of the patient's knee joint based on the data provided by the gloves and gradually increase the intensity of the exercises accordingly. The motion capture gloves from Noitom are shown in **Figure 6**.

Figure 6. The motion capture gloves from noitom.

As the technology of Perception Neuron™ Studio continues to evolve, its application in rehabilitation medicine will become increasingly widespread. In the future, with the integration of artificial intelligence and big data analysis, the system can further optimize personalized rehabilitation training plans through deep learning. Combining virtual reality and augmented reality technologies, the rehabilitation process can not only provide precise data support but also offer a more intuitive and immersive experience for patients, enhancing their engagement and improving treatment outcomes. The usage diagram of Noitom's Perception Neuron™ series products is shown in **Figure 7**.

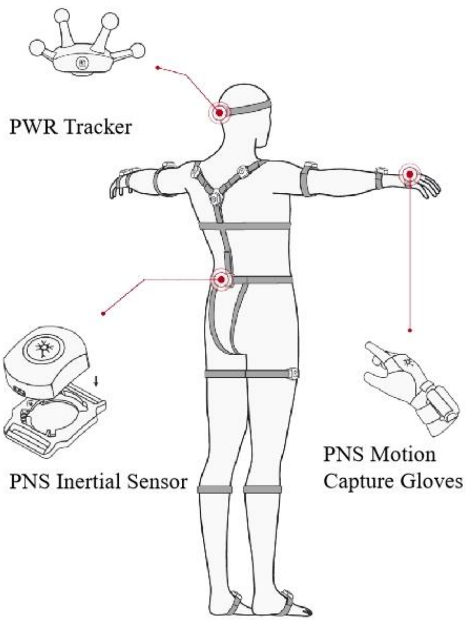

Figure 7. The usage diagram of noitom's perception neuron™ series products.

5. Conclusion

This study proposes a novel posture detection and analysis method based on sensor fusion embedded electronic systems, aimed at improving the accuracy and real-time performance of human movement monitoring. By integrating data from accelerators, gyroscopes, and magnetometers, and employing the Almanac filter algorithm for sensor data fusion, the system effectively eliminates errors from individual sensors in pose recognition, thereby enhancing the system's reliability and accuracy.

In practical applications, this system can precisely capture multidimensional movement data from the human body and perform detailed bio-mechanical analysis of the movement process. Experimental comparisons validate the effectiveness of the proposed system across different motion scenarios, including daily activities, sports, and rehabilitation training, demonstrating superior performance. The system can provide real-time posture feedback, helping doctors, rehabilitation therapists, and athletes make better adjustments to their movements and monitor health.

Furthermore, this study explores the potential development directions for sensor fusion technology in biomedical engineering. With the continuous advancement of sensor technology and embedded systems, the accuracy of posture detection and the intelligence of the system can be further improved, providing more effective technical support for personalized medical care, rehabilitation treatment, and health management.

In conclusion, the proposed sensor fusion-based embedded electronic system offers a new approach and methodology for human posture detection and bio-mechanical analysis, with broad application prospects. There is still room for further research in areas such as algorithm optimization, system cost reduction, and improving user experience. It is expected that this technology will be more widely applied in the fields of medical care and sports health in the future.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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