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Human motion state recognition based on MEMS sensors and Zigbee network

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ABSTRACT

This article is to study the system structure scheme based on Zigbee wireless transmission, and complete the overall design of the system scheme on this basis. Human motion capture systems are widely used in the creation of film and television works, motion analysis, video games, rehabilitation medicine and other fields. This article discusses the design and implementation of a human motion capture system based on MEMS sensors and Zigbee networks. The system can be installed on the human body Multiple sensor nodes in various parts obtain the movement information of the human body, and use sensor network technology to aggregate these data and upload them to the host computer. First, this article introduces the characteristics of angular velocity sensors, acceleration sensors, magneto resistive sensors and Zigbee networks. Then, this article explains the overall structure of the system, and from a theoretical point of view, explains how the system uses angular velocity sensors, acceleration sensors, magneto resistive sensors and Zigbee networks to achieve human motion capture. This part focuses on including vector observation methods and angular velocity Two posture capture methods including the integration method, and their advantages and disadvantages are analyzed. To achieve the complementary advantages of the two algorithms, a data fusion algorithm based on complementary filtering is introduced and optimized appropriately. In addition, this article also introduces the networking principles and optimization schemes of the Zigbee network in this section. After this, this article explains in detail the system hardware structure, chip selection scheme, circuit design scheme, software workflow and implementation of core programs Method. Finally, this article shows the effect of the actual work of the system, and compares it with the theory to verify the feasibility of the theory. Based on the research of MEMS sensor measurement unit and algorithm, a Zigbee-based wireless transmission test system was established. LabVIEW software with functions of data reception, attitude angle calculation, trajectory calculation, eigenvalue extraction, BP neural network recognition, display and data saving was designed and tested the whole system functions. The test results show that the wireless data transmission of Zigbee network is normal, the data detection and processing programs of the host computer are stable, and the correct identification of the human body's motion state can be realized. The results show that compared with the existing research, our research has increased its efficiency by 10%, and its accuracy has increased by nearly 15%.

1. Introduction

With the rapid development of computer technology, intelligent frameworks, and pervasive computing, and an efficient way of human–computer interaction, play an increasingly important role in our lives. The study of gesture recognition has a very important position in human–computer interaction. Pose recognition is a process in which the user makes a pose that can be perceived and reconstructed by the receiver. A pose is a meaningful body movement, including physical movements of the fingers, head, face, or body [1,2]. These physical movements not only convey meaningful information but also interact with the environment. Currently, human body posture recognition has a wide range of applications in the smart home, smart medical, and gaming interactions [3]. In the smart home, many smart appliances need to be controlled by human postures, such as controlling the music volume, light, and darkness of the home through gestures. In smart healthcare, diagnostic and therapeutic support for healthcare and rehabilitation training can be provided by tracking patient behavior and analyzing patient movement data [4]. Posture recognition can also monitor abnormal patient behaviors such as falls and unconsciousness to enable medical personnel to take timely action in crises. In many virtual reality game products, human posture needs to be displayed in the virtual world of the game to enhance the user experience by increasing the interaction between the computer and the human body [5]. Deep learning has made breakthroughs in speech recognition, image recognition and other fields. The full name of deep learning is deep neural network, which is essentially a multi-level artificial neural network algorithm, which simulates the operating mechanism of the human brain from the structure, and simulates the operating

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mechanism of the human brain from the most basic unit. Deep learning has begun to make breakthroughs in the fields of computer vision, speech recognition, and natural language understanding. In the field of speech recognition, in 2010, the recognition error rate of speech recognition using deep neural network models was reduced by more than 20% compared with the traditional Gaussian mixture model. All current commercial speech recognition algorithms are based on deep learning. In the field of image classification, the classification accuracy of the current algorithm for the ImageNet data set has reached more than 95%, which is comparable to the resolution ability of humans. Deep learning has also made breakthrough progress in the fields of face recognition, general object detection, image semantic segmentation, and natural language understanding.

In the era of big data, with the continuous development of science and technology, many exciting results have been obtained in the research of human motion and posture [6,7]. This direction has become a highly comprehensive cross research topic, and has been widely used in daily life and cutting-edge military field. In recent years, researchers have carried out in-depth research on the collection of human motion characteristic information, such as human voice, acceleration, iris characteristics, myoelectric voltage and other characteristic signals, and analyzed and preprocessed the characteristic signals through existing technical means to obtain motion parameters and carry out motion recognition [8,9]. With the development of MEMS inertial sensors, and the growing maturity of embedded technology and wireless sensor network technology, it is possible to capture and detect human motion based on inertial sensors. The human motion capture and detection system based on inertial sensor has little interference to the wearer's motion, which makes the movement closer to the normal situation and the detected data more real and reliable. Therefore, the human motion capture and detection method based on MEMS wearable inertial sensor has become an important direction of current application development. However, the MEMS gyroscope has drift error, and the attitude Angle will have a large cumulative error when used for a long time. Because of these problems, the current human motion capture and detection methods based on MEMS wearable inertial sensors have such problems as low recognition rate and large error. Based on this, this paper intends to combine MEMS inertial sensor technology with Zigbee wireless network technology to study high-precision attitude Angle calculation method and detection system, in order to achieve efficient recognition of human motion state. The main contributions of this paper are as follows:

(1) We introduce two attitude capture methods: vector observation method and angular velocity method, and analyze their advantages and disadvantages.
(2) We introduce a data fusion algorithm based on complementary filtering and optimize the algorithm appropriately.
(3) This paper studies a human motion capture system based on MEMS sensor and Zigbee network. The system can be installed in multiple sensor nodes in each part of the human body to obtain human movement information, and use sensor network technology to aggregate these data and upload to the upper computer.
(4) This paper shows the actual working effect of the system and verifies the feasibility of the theory by comparing it with the theory.

The rest of the paper is organized as follows: In Section 2, references related to MEMS sensors, Zigbee networks and human motion state recognition have been analyzed; In Section 3, we focus on MEMS Sensors and Zigbee Networks for Human Motion Design; In Section 4, we devote to the analysis of system performance and the results human motion state recognition; In Section 4, we summarize and forecast the work in this paper.

2. Related work

Also, posture recognition can be applied to developing hearing aids for the hearing impaired, recognizing sign language, lie detection, distance learning, and distance learning assistance [10,11]. MEMS contains sensors, mechanical structures, signal processing, and control circuits, and other modules, it uses the material is mainly semiconductor. MEMS includes not only a variety of disciplines such as medicine, chemistry, physics, optics, and materials science, but also a variety of engineering technologies such as electrical engineering, bioengineering, information engineering, and mechanical engineering. As people are increasingly concerned about their health, the medical industry will gain tremendous growth, and the combination of ZigBee technology and medical health will have great economic value and good market prospects in the future [12].

Liang et al. used a multi-view geometry approach and extended the trajectory formed by 13 skeletal points to recognize actions down a dynamic scene [13]. Allahham et al. used 15 skeletal points to form a human pose and created a Gaussian distribution for each point to increase the robustness of the pose expression, and then recognized the action category through a linear sequence of changes [14]. With the development of neural networks on computer vision, increasingly deep learning-based human action recognition featuring human structure has achieved better results, and Toshiyoshi et al. used convolutional neural networks to learn the skeletal point hierarchical feature approach and identify action categories using the fusion of high-dimensional features [15]. The above methods are all based on the spatial coordinates of human skeletal points that have been obtained, and human structural features can be extracted from the estimated skeletal point data by first estimating human skeletal points through the human posture estimation algorithm, in addition to being obtained directly from the skeletal point information [16]. Thakur et al. detected human skeletal points through depth images captured by a depth camera, and then used the skeletal points in time, differences in the spatial domain to get the overall dynamic changes and identify human body movements based on these changes [17]. Li et al. first used the open pose method to estimate the coordinates of human skeletal points in 2D images, and then used graph convolutional networks to learn the structural features of the human body and identify them [18]. Mosenia et al. used sports videos as the object of study by calculating the video [19]. The global features of the optical flow method are not strongly dependent on the spatial contour extraction fine-grained of the human body, and the background interference is small, so the algorithm has good generalizability and robustness [20,21].

Affected by factors such as gyroscopic drift error and motion acceleration, MEMS sensor-based human motion capture and detection methods often suffer from large attitude angle solving error and low motion state recognition rate. In this paper, based on the Kalman filtering principle, it is proposed to fuse the detection information of MEMS gyroscope, accelerometer, and magnetometer, take the attitude angle of the output of the attitude reference system as a reference and use the Kalman filtering algorithm to correct the output of the inertial system, to achieve a better estimation of the human body motion attitude angle. A Kalman filtering algorithm based on the pre-estimation of motion acceleration is developed to adjust the variance of the measured noise, which weakens the effect of motion acceleration on the attitude reference system. To address the problem of the low recognition rate of traditional methods, this paper also proposes to study a better motion feature extraction method to improve the recognition rate of human body motion. To address the drift error and motion acceleration of MEMS gyroscope, which leads to the low accuracy of attitude angle estimation, the paper proposes to develop a high-precision attitude angle solver. The Kalman filtering algorithm is used to combine the inertial system and the attitude reference system to improve the accuracy of the attitude angle calculation. According to the magnitude of the carrier motion acceleration, the magnitude of the measured noise variance of the Kalman filter is adjusted to weaken the influence of the motion acceleration on the accuracy of attitude angle solving in the Kalman filtering process. Establish the human body motion model, give the equation and trajectory error model for each joint motion trajectory calculation, and analyze the influence of attitude angle error on the accuracy of wrist joint trajectory calculation. Test the overall function of the human body motion state measurement and recognition system.

3. MEMS sensors and Zigbee networks for human motion design

3.1. MEMS sensor-based motion design for the human body

Different types of sensors have different sensitivities, and we can take advantage of this difference in sensor sensitivity to improve tracking accuracy. In our system, the sensitivity of the accelerometer and gyroscope sensors is not the same, since we mainly use the acceleration to calculate the displacement of the wearable device, so we only focus on the sensitivity of the inertial accelerometer measurement axis [22]. Let us start with the concept of sensor sensitivity, which is defined as the ratio of the change in voltage input to the change in output, given a constant operating condition. It is usually desired that the sensor be highly sensitive and constant, i.e., that the input and output characteristics of the sensor be linear. The sensitivity of the sensor is usually chosen in conjunction with the needs of the entire moving process to enable the sensor to cover the entire measurement range, thus improving the utilization of the measurement circuit and maximizing the measurement accuracy of the sensor, as shown in Fig. 1.

Since the sensitivity of each measurement axis is different in different directions, we can see that there is a tendency for the position of the calculated coordinates to be different as well. To eliminate such differences, for each measurement axis of each sensor, we do the following. Zigbee is an emerging short-distance, low-rate wireless network technology. It is a technical solution between wireless marking technology and Bluetooth. It has its own radio standard, which coordinates communication among thousands of tiny sensors. These sensors require very little energy to transmit data from one sensor to another via radio waves in a relay manner, so their communication efficiency is very high. For each sensor, we will calculate the sensitivity correction factor for each axis, since each wearable device is fixed to the human joints, its movement trajectory will also meet the human body model, as we also mentioned earlier, the human body model can be simplified to a multi-mass model, the human torso can be divided into 6 joints, and in our system, it is the MEMS inertial sensors fixed to the human body of these joints of the human body is by certain correlations and limitations, so we can use these correlations and limitations to further optimize the tracking accuracy [23].

Among the various types of MEMS sensors, MEMS motion sensor has the most extensive application, which can be further divided into three categories: gyroscopes, accelerometers, and magnetometers [24]. A triaxial accelerometer can output acceleration in any direction, a gyroscope measures the physical measure of rotational angular velocity in deflection and tilt, and a magnetometer measures the strength of the magnetic field. For example, accelerometers and gyros can be combined to form 6-axis inertial sensors; electronic compasses are formed by combining magnetometers and accelerometers; and with the development of MEMS technology, accelerometers, gyros, and magnetometers can be integrated into 9-axis sensors. Human posture is made up of a series of body movements, and to recognize posture, information about the body's movements needs to be captured, so the sensors we use in this paper should also include accelerometers, gyroscopes, and magnetometers.

Once we have the coordinates of each sensor placed on the joints of the human body, we can identify the human body pose, assuming that a pose is obtained by n sensors, then each pose is a vector of 3N, this is because each sensor has displacement data in the X, Y and Z axes. Since the hardware will inevitably generate mechanical errors during the manufacturing process, these errors will continue to affect our data, and our motion data will also be affected by high-frequency random noise and gravity during the acquisition process, so we need to denoise the motion data. The bottom layer of the Zigbee wireless transmission solution is the media access layer and the physical layer that adopt the IEEE 802.15.4 standard. The main features are low speed, low power consumption, low cost, support for many online nodes, support for multiple online topologies, low complexity, fast, reliable, and safe.

Ideally, the X, Y and Z axes in the accelerometer of a MEMS inertial sensor are orthogonal to each other. However, this is not the case because mechanical errors are unavoidable and must cause alignment errors. There are two typical forms of alignment error, one is the shaft to package alignment error and the other is the shaft-to-shaft alignment error. The shaft to package alignment error refers to the encapsulation process, because the solder pins cannot adhere to the circuit board, and the surface of the circuit board there will be a certain curvature is not completely flat, resulting in the measurement axis of the sensor internal offset error.

3.2. Zigbee network design analysis for human motion

The ZigBee chip on the market is just a PHY layer standard chip, which has a single function and can only modulate and demodulate wireless communication signals, so it must be combined with a microcontroller to achieve the protocol and data transmission and other functions [25]. Also, the single-chip solution only integrates the single-chip part with the RF part, no longer need an additional single-chip, the advantage is to save costs and simplify the design circuit, but this single-chip solution does not contain the ZigBee protocol. For users doing practical applications, the workload of these two solutions is too large, the development cycle and test cycle are too long, and, because of the development of wireless devices, it is not easy to guarantee the quality of its products.

The gateway system mainly consists of an embedded gateway and a ZigBee coordinator. The embedded platform uses the development board, which has a wealth of interfaces and fully meets the design needs. At the same time on-chip resource-rich, while reducing the cost of the system while reducing the difficulty of hardware design. ZigBee coordinator using chip. The block diagram of the entire system shown in Fig. 2.

Z-stacks function is in the file, in general, it only does two jobs, one is to initialize the system, that is, the boot code to complete the initialization of the software architecture and hardware system required for each functional module, to prepare for the operation of the operating system, which is mainly divided into initializing the system clock, detecting whether the chip voltage is normal, initializing the stack, configuring the system timer, initializing the chip, and so on. Each hardware module, initialize memory and initialize the operating system; the second is to start executing the operating system entity part, which has only one line of code operating system, the function is the main part of the polling operating system, the main function is to constantly query each task whether there are events, if so, then execute the corresponding function, otherwise, query the next task. We are now using the best found through our continuous testing. The ZigBee motion nodes used in this paper all contain 3 sensors, namely accelerometer, gyroscope, and magnetometer, which collect the sensor data in real-time and send the data to the ZigBee coordinator via ZigBee wireless network, then the coordinator sends the data to the gateway via serial port, and the gateway transmits it to the PC terminal via Ethernet interface for further processing. Conversely, the PC terminal can also send some control or query commands to control the end nodes or get the required information. In the ZigBee network, the coordinator is the convergence point of the data flow of the whole network, so to solve the interoperability problem between the ZigBee network and Ethernet, it is only necessary to define a feasible communication protocol between the

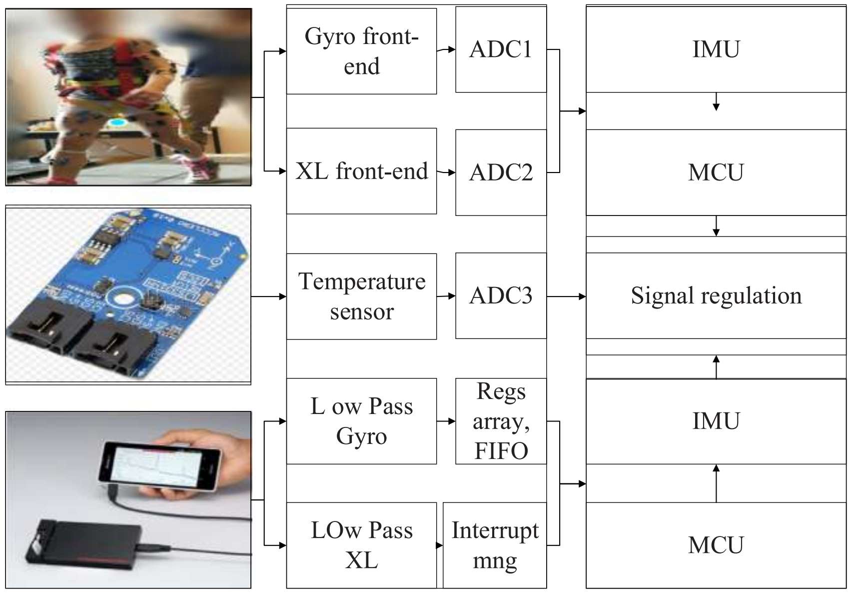

Fig. 1. MEMS sensor-based human motion module.

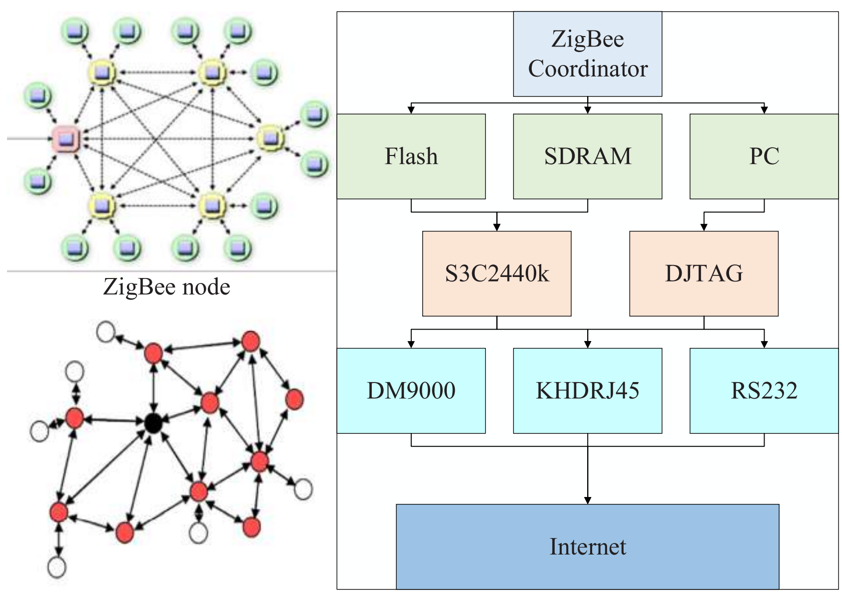

Fig. 2. Hardware connection diagram of the gateway system.

coordinator and the gateway. The challenge of using MEMS and Zigbee to recognize human movements is how to recognize human movements more accurately and obtain results quickly.

For the sake of cost and the simple and lightweight protocol, this paper uses the serial port to connect the coordinator and the gateway, and the asynchronous serial port communication is used between the coordinator and the gateway. The gateway adopts the Client/Server mode of network communication. One side listens to the data from the Internet through the Socket, processes the received IP packets, and converts them into serial port packets to be sent to the ZigBee coordinator; the other side listens to the serial port, processes the packets from the serial port, and converts them into IP packets to be sent to the Internet client. In a ZigBee wireless network, devices have two different addresses: a 16-bit network address and a 64-bit IEEE address (physical address). Sensitivity analysis method is to find out the sensitive factors that have an important impact on the economic performance indicators of the investment project from the many uncertain factors, and analyze and calculate the degree of influence and sensitivity on the economic performance indicators of the project, and then judge the project an uncertainty analysis method of risk tolerance. Sensitivity analysis helps determine which risks have the greatest potential impact on the project. It keeps all other uncertain factors under the condition of the benchmark value, and examines how much the uncertainty of each element of the project affects the target. The 16-bit network address is assigned by the coordinator when the device joins the ZigBee network, which is unique in this ZigBee network. The 16-bit network address has two main functions: to identify different devices in the network and to specify the destination address and source address for data transmission in the network. The 64-bit physical address is set by the manufacturer according to the IEEE standard when the device is shipped from the factory, of course, users can also modify the physical address of the device through the programming software SmartArt Flash Programmer.

On one hand, if you want to control a node in the ZigBee network remotely, you must know the address of the node, but the IP application layer does not know the network address of the node in the ZigBee network, so you can usually use the globally unique physical address as the destination address. On the other hand, the topology of the ZigBee network may change due to some unexpected factors, and the network address of the node may also change, so the network address is less stable. However, in the ZigBee network, all nodes transmit data through the network address, so that the routing algorithm can be used to find the best path to speed up data transmission and reduce the power consumption of nodes. To solve this address conflict problem, the communication protocol must define a specification for the conversion between the physical address and the network address of ZigBee nodes.

3.3. MEMS sensor and Zigbee network-based system design

Behavior recognition aims to identify the behavior of experimental subjects from the observation and analysis of the behavior of a series of experimental subjects. With the rapid expansion of the smartphone market and the rapid development of miniature sensors, a wide variety of MEMS sensor devices are embedded in human smartphones, and human activity can be effectively detected using the sensor information in smart devices. Now that the use of smartphones to detect human activity will become the norm, researchers have been able to collect sensor information from mobile device settings to enable services such as health detection, motion tracking, elderly monitoring, and smart home. Human behavior recognition algorithms can be broadly categorized into two types: machine learning-based recognition algorithms and neural network-based recognition algorithms. We randomly allocate 80% and 20% of the data set, where 80% of the data is used as the training set, and 20% of the data is used as the test set. The machine learning-based human behavior recognition algorithm in early research flow is built a complete human behavior recognition model through feature extraction engineering and algorithm construction, while the neural network-based human behavior recognition model automatically extracts feature sets through neural network training and builds a complete human behavior recognition model through network training and neural network. The appropriate solution is selected according to the actual situation, as shown in Fig. 3.

After passing the data acquisition module, the original sensor data information is obtained, and the original data will be mixed with some useless sharp noise due to human factors or inherent signal reasons in the equipment, these burr noises will interfere with the post-sequence modeling identification and reduce the performance of the subsequent identification model. Therefore, some noise reduction and standardization measures need to be carried out on the sensor sample data after data acquisition. The traditional machine learning methods all require a priori knowledge to perform manual feature extraction of sequence information, and the time domain based features include mean, variance, root mean square, standard deviation, bias, maximum value, minimum value, median, mean absolute deviation, kurtosis, quartiles, and range values, and the frequency domain based features include frequency response coefficient, spectral energy, spectral entropy, and power density. Algorithm design is the most core part of behavior recognition. According to the feature set obtained before, the recognition accuracy obtained through different algorithms is not the same, and by designing suitable algorithms, it is possible to ensure that the classifier model obtained from behavior recognition has high universality and high accuracy.

The human behavior recognition based on intelligent equipment is to analyze and process the pre-collected data, and carry out the classification recognition through a certain algorithm so that the classification algorithm has high universality and high accuracy. We use 3 layers for the hidden layer and one layer for the output layer. The human behavior recognition involved in this paper is built based on neural network, abandoning the traditional human behavior recognition method based on machine learning, starting from the perspective of the neural network, using the neural network input raw data, automatically extracting an effective set of features to complete the identification of human behavioral activities. The purpose of this paper is to realize the classification and recognition of human behaviors based on sensor devices and human daily behaviors and falls, and thus this paper will design a system solution for human behavior classification. The experimental system mainly implements human behavior recognition based on the android platform, which mainly provides certain early warning for the fall activities in human behavior recognition.

The system uses cloud computing storage technology for mobile phone software design to improve the fall detection system's fall history data recording function, and analyze and process the alarm information, improve the scope of mobile phone software application promotion in social networks, maintain high tightness between the service quality of the product and the user, and meet the comfort of user experience. Using cloud computing technology application, the mobile phone real-time acquisition acceleration sensor is sent to the background for fall judgment, when the mobile phone terminal software analyzes and processes the front-end fall detector's location information, the faller's information is sent to the remote server or mobile phone, and the location information is processed quickly and effectively. The client is mainly responsible for sensor data collection, data packaging, local data preservation, and uploading to the server, while the server is mainly responsible for certain pre-processing of the client's data, as well as training and action recognition of the algorithm model. The behavior recognition system framework, behavior recognition algorithm model, and experimental system model architecture are introduced separately. First, this chapter provides a detailed description of the process of human behavior recognition, including the machine learning-based human behavior recognition model and the neural network-based human behavior recognition. Second, the overall framework for the algorithms designed for this paper is described in detail. Finally, the experimental system model architecture is described for this paper.

4. Analysis of results

4.1. System performance results analysis

Firstly, the communication throughput of the terminal motion node is tested, which directly affects the sampling rate of the sensor data of the motion node, i.e., the number of motion-sensing data packets collected per unit time, which has a great influence on the accuracy of the result of multi-sensor data fusion. Firstly, the network is built automatically by the ZigBee coordinator and one ZigBee terminal motion node. Secondly, the PC terminal sends fixed size data packets periodically to the terminal motion node via serial port debugging assistant and sends them to the coordinator via ZigBee wireless network, and then the coordinator sends the data to the serial port debugging at the PC terminal via the serial port. The assistant shows that each test takes 10 min. Then, the interval between sending data is gradually reduced until packet loss occurs, at which point the communication rate is the maximum throughput. Receive data for verification through the serial port debugging assistant on the PC terminal, and the specific data throughput is shown in Fig. 4.

From Fig. 4, the network throughput is maximum when the packet size is 45 bytes, which has a value of 26.47 kbps, which is the reason the packet size is set to 45 bytes when designing the gateway communication protocol. For the coordinator node, the specific test method is as follows: let the coordinator node network with 1, 2, and 3 end-movement nodes respectively, and then make all the end-movement nodes send data to the coordinator at the same time at the maximum communication rate. The test time is 30 min. The experimental results of network throughput for different packet lengths are shown in Fig. 4, and there is no significant correlation between the ZigBee network throughput and the number of end-movement nodes. The total time taken for a single packet to be transmitted in a ZigBee network is about 7 ms, so the theoretical maximum throughput for a single-hop transmission in a light-load, non-beacon enabled single-domain network is about 115.5 kbps. However, in actual applications, the

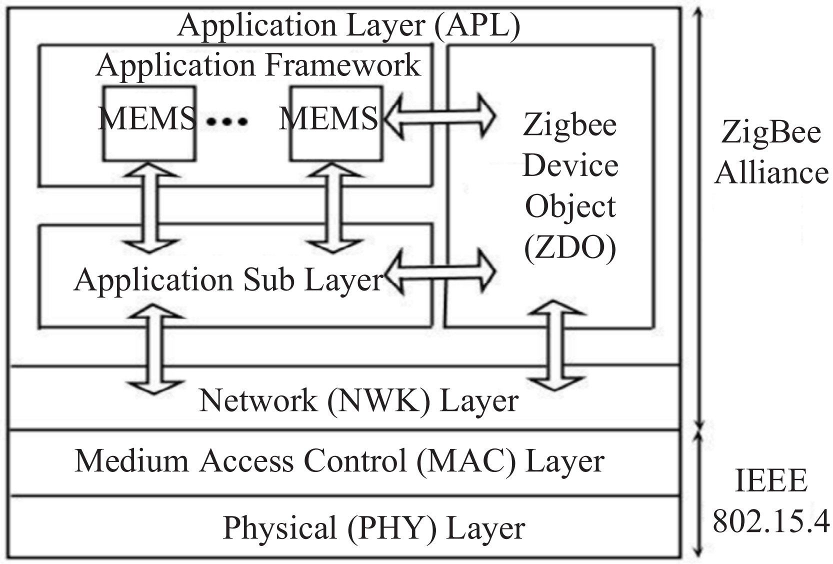

Fig. 3. MEMS sensor and Zigbee network-based system framework.

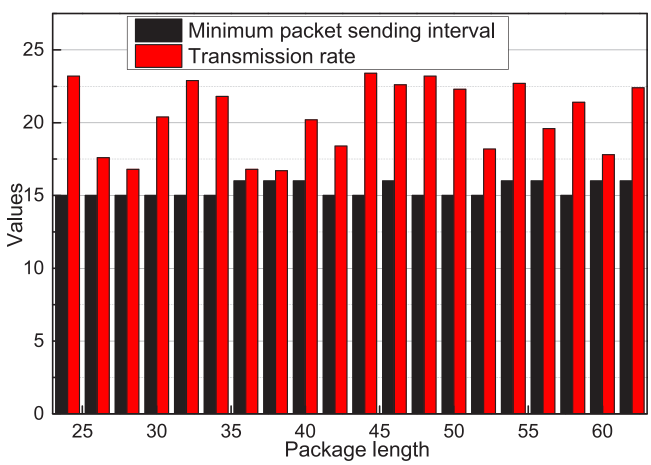

Fig. 4. Point-to-Point Transmission Rate Summary.

gap between the actual throughput and the theoretical data is large. We sorted out the main postures of the human body and found that there are about 40 types that are relatively common. Because our current technology is not mature enough, ours is only to study these 40 postures. Our research found that the accuracy of the recognition algorithm is still very high. This is mainly due to the existence of energy-saving function, low power consumption function, encryption function, and delay retransmission function due to electromagnetic waves in the ZigBee protocol stack. The maximum communication throughput finally measured in this paper is 26.47 kbps, which is more throughput in the same situation and meets the requirements of this project.

To check the effectiveness of the Kalman filtering algorithm, the practical effects of attitude solving are tested and analyzed in this paper. The pitch, roll, and yaw angles of the object in the range of −5° to −35° are measured by a protractor and compared and analyzed with the real-time solved angles on a PC host computer to verify the accuracy of the system's solved angles. The measured and solved angles are compared to calculate the angle error of the system to evaluate the performance of the whole system. The experimental results are shown in Fig. 5.

The accuracy of the final solution is within 1.22° for pitch angle, 1.27° for roll angle, and 2.61° for yaw angle, which is larger than the pitch and roll angle, mainly due to magnetic interference on the motion module. Overall, however, the accuracy of the entire attitude display system met the design requirements. At 10° intervals, the module rotation angle refers to the difference between any two adjacent solved angles. As shown in Fig. 5, the error between the module rotation angle and the actual rotation angle of 10° is within 2°.

The error is larger compared to Fig. 4 because the data processing of the motion sensor is mainly reflected in the calculation of the angle between the two vectors in the three-dimensional coordinate system, in three-dimensional space, the angle between the two vectors cannot determine the direction of rotation, so the angle can only be between 0–180°. Two motion vectors without coplanar constraints, so the calculated angle there is no coplanar error.

The PC terminal posture monitoring host software can receive motion sensor data in real-time and display node information and node status in real-time. By binding the device and the corresponding joint, it is found that the motion posture of the terminal motion node is synchronized with the posture in the three-dimensional display of joint mobility with small error. The intermediate presentation layer of expanded performance is to open a variety of different front-end training software frameworks and a variety of different back-end expression bridges in deep learning calculations, so that the deep learning network model compiler can more effectively optimize and infer between the two. In the deep learning network model compiler, the core idea of the middle presentation layer draws on the LLVM architecture design, and the newly added exclusive middleware is an important description method for solving the inference-side model running on different hardware platforms. The current intermediate presentation layer of the deep learning network model compiler is mainly divided into two camps, NNVM/TVM and TensorFlow XLA, but in fact, model exchange formats such as ONNX and NNEF are also various definitions of the intermediate layer. The industry consensus "IR" competition will be an important part of the future software framework dispute. The commands sent to the end motion nodes by the PC terminal are answered with correct data, which proves the accuracy and reliability of the downstream data transmission of the gateway communication protocol. In summary, the gateway protocol designed and implemented in this paper is stable and reliable.

The Zigbee gateway system is tested for its functionality, including the data transmission efficiency of the ZigBee network, network throughput, and terminal node power consumption. The effectiveness, reliability, and stability of the gateway protocol are tested and verified. Finally, the effect of multi-sensor data fusion is tested by the PC

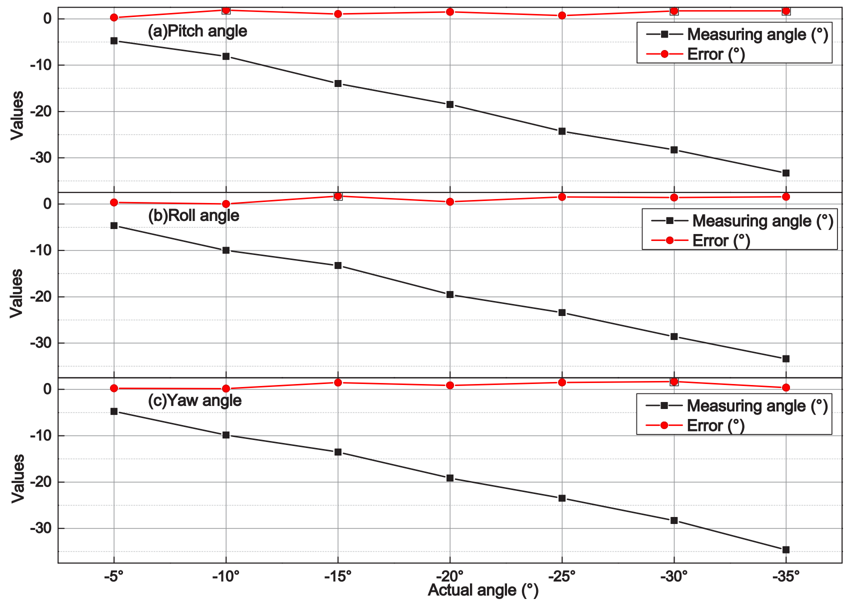

Fig. 5. Pitch angle, roll angle, yaw angle test comparison chart.

terminal attitude monitoring software of the gateway device to verify the effectiveness of the Kalman filtering algorithm, and the final test results meet the project design requirements.

4.2. Analysis of human movement state recognition results

This section will explore the accuracy of limb tracking. In our experiments, it was the placement of sensors on the human wrist, elbow, and shoulder joints, with five different subjects, for a total of 40 sets of postures tested. In turn, we distinguished between large and small magnitude postures based on the magnitude of the posture. The absolute error of posture tracking is the difference between the displacement values calculated using the actual measurements and the displacement values calculated using our algorithm. The relative error of pose tracking is the ratio of the displacement value calculated using the actual measured displacement value and the displacement value calculated using our algorithm, as shown in Fig. 6.

The tracking accuracy of all the poses is first analyzed. Fig. 6 represents the absolute and relative error cumulative distribution plots for all poses. The red line represents the results of the basic limb tracking algorithm, the green line represents the results of the improved Algorithm 1 that uses the sensor sensitivity difference to improve tracking accuracy, and the blue line represents the results of the improved Algorithm 2 that uses both the sensor sensitivity difference to improve accuracy and the linkage and limitations of human joints to improve tracking accuracy on the basic limb tracking algorithm. We can see from the figure that the basic tracking accuracy is the worst, its average tracking accuracy is 0.075 m, after using our improved algorithm, the tracking accuracy can reach 0.06 m. The experimental results show that for all postures, the tracking accuracy can be improved by 15% after using the two improved algorithms. Compared with other research models, our model has greatly improved its efficiency and accuracy.

We will discuss the effect of pose amplitude on limb tracking accuracy in the future. Fig. 7 shows the cumulative distribution function plots of absolute tracking accuracy and the cumulative density distribution plots of relative tracking accuracy for small amplitude poses, respectively. Similarly, the red lines represent the results of the basic tracking algorithm, while the green represents the results of Improved Algorithm I, and the blue represents the results of using both Improved Algorithms I and Improved Algorithm II. Considering other trajectories will make the system and the factors to be considered more complicated. We cannot consider other trajectories yet. From the two plots, for small amplitude poses, it is the basic tracking algorithm that has the worst accuracy, while the sensor sensitivity improvement method alone has the best accuracy.

We can conclude from the figure that for a large pose, the best tracking accuracy is obtained by using both improvement algorithms, while for a small pose, the highest accuracy is obtained by using only the sensor sensitivity improvement algorithm. The reason is as follows: for the improved algorithm two, we mainly use the connection and limitation between human joints to avoid some abnormal results that exceed the limit range of human joints, but in the small-amplitude pose, the results will not exceed these limits, so using this method does not improve the tracking accuracy.

Therefore, in practice, for most scenarios, we recommend using both methods to improve tracking accuracy, but for some scenarios that only include small-amplitude poses, we recommend using only the sensitivity of the sensor to improve tracking accuracy.

At present, artificial intelligence algorithms based on deep learning are mainly implemented by relying on computer technology architecture, and deep learning algorithms are encapsulated in software framework 1 for developers to use. The software framework is the core of the entire technical system, which realizes the encapsulation of artificial intelligence algorithms, the call of data, and the scheduling and use of computing resources. To improve the efficiency of algorithm implementation, its compiler and underlying hardware technology have also been optimized.

As the training process shown in Fig. 8, the dashed line is the accuracy curve, where the purple dashed line is the curve where the classification accuracy of the training set increases with the number of training rounds, the blue dashed line is the curve where the classification accuracy of the validation set increases with the number of training rounds; the solid line is the loss function curve, where the red solid line is the curve where the loss function of the training set increases with the number of training rounds, the green solid line is the curve where the loss function of the validation set increases with the number of training rounds. The graph shows the curve of the change as the number of training rounds increases. The horizontal axis is the number of training rounds, the left vertical axis is the measure of accuracy, and the right vertical axis is the measure of the loss function. From (a), (b), (c), we can see that the loss function decreases during training, the recognition accuracy increases, and the model completes convergence, but there are still some differences in the convergence process of the diagram, (c) is the fastest convergence, the curve is relatively smooth. It can converge

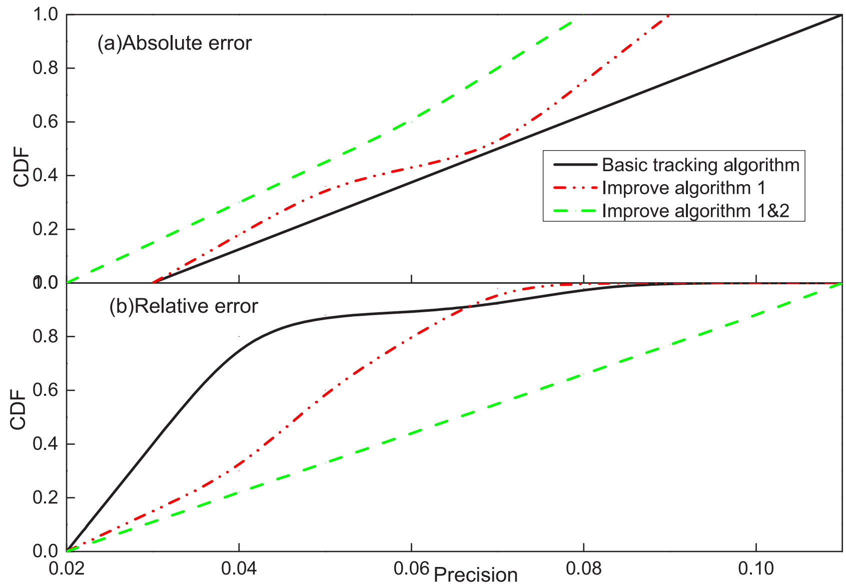

Fig. 6. Cumulative distribution function of absolute and relative errors for all poses.

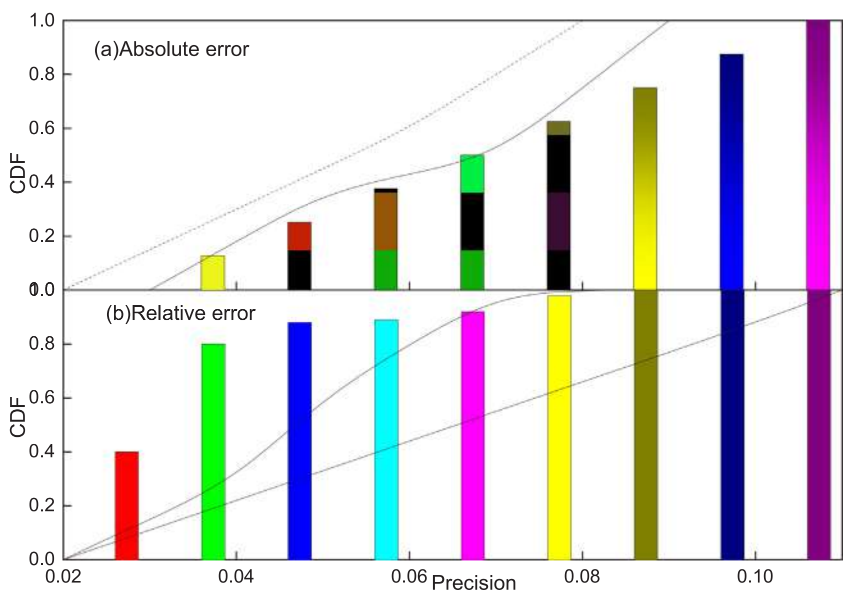

Fig. 7. Cumulative distribution function plot of absolute and relative errors for large-amplitude pose.

but slowly, the curve is more oscillating, and from the dataset point of view, the actions in the AS2 subset are more similar and the differences between classes are small, so the model converges slowly. Therefore, it can be proved that different subsets of actions will have some influence on the training process and result of the model. From (c), (d), (e), we can see that the loss function decreases during training, the recognition accuracy increases, and the model converges. Comparison of oscillation and the final training set and test set loss function values differ widely, from data division mode, the validation set and test set in Experiment 3 used different action executor actions, making the same action on the class differences are relatively large.

In the experimental setup part, tests are conducted on three public datasets, in which the sanctioned dataset is divided into three subsets for training, and three validation tests are conducted according to different ways of dividing training data and test data, and the Florence-Action and Gutknecht-Action datasets are verified by cross-validation. By comparing with the existing literature, it is learned that the fusion of vector mode ratio and vector angle fusion is the best, which verifies that feature extraction can better identify human movements based on skeletal points.

5. Conclusion

In this article, we have designed and established a human motion state measurement and recognition system based on MEMS sensors and Zigbee network. In this system, we use a star-shaped network topology with simple structure and high data transmission rate. And according to the magnitude of the carrier motion acceleration, the magnitude of the measured noise variance of the Kalman filter is adjusted at the right time, which weakens the influence of motion acceleration on the accuracy of attitude angle solving during the Kalman filtering process. The method not only overcomes the influence of the carrier motion acceleration but also compensates for the cumulative error of the inertial system and achieves a higher accuracy of attitude angle solving compared to the classical Kalman filtering algorithm. In this paper, the human body motion measurement and recognition method based on

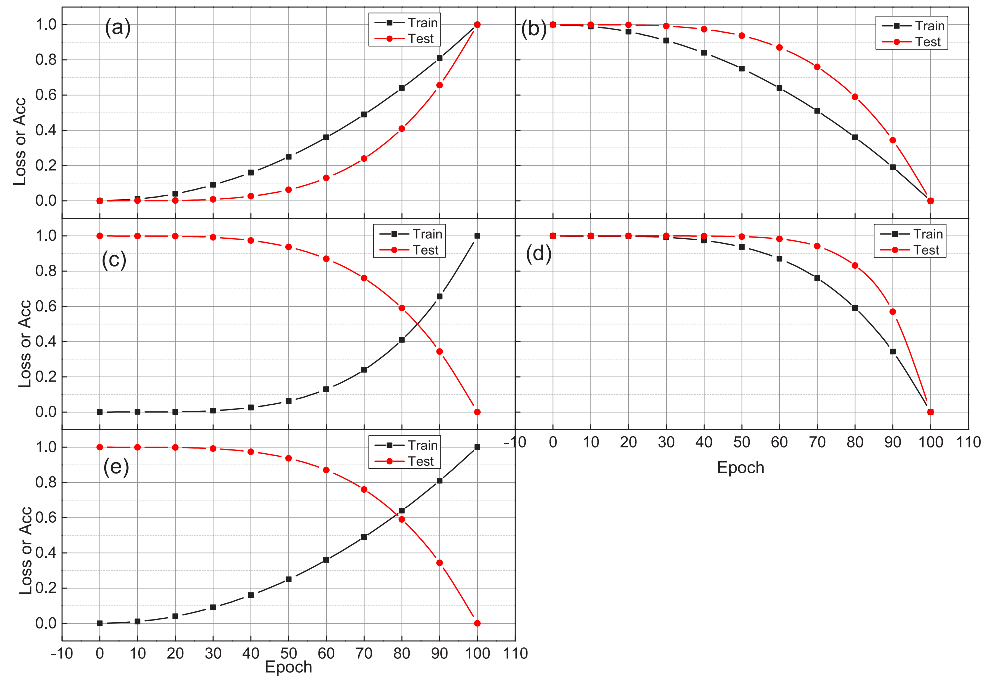

Fig. 8. Model training loss function, accuracy change chart.

MEMS sensors are not only simple to use and easy to install, but also has feasibility and validity once the recognition rate is high. And its efficiency has increased by 10%, and its accuracy has increased by 15%, which will have important meanings for future practical applications. Through the actual test, the system works normally. The high-precision attitude angle solving method is studied. In the future, we will study other trajectories or multiple trajectories.

CRediT authorship contribution statement

Qing Liu: Performed the formal analysis, Wrote the manuscript.

Declaration of competing interest

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

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