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Multi-sensor Data Fusion Hand-made Teaching System for Preschool Education

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Abstract: With the rapid development of the information technology industry, personal computers, smart phones, home appliances and other equipment are more and more popular with the public, and human-computer interaction is becoming more and more important in production and daily life. As one of the leading technologies in human-computer interaction, body motion detection technology is used in medical, education, security, entertainment and other fields. This article introduces the technology of multi-sensor number fusion to study the hand-made teaching in preschool education. In this paper, the selection of magnetic sensors is improved for the multi-sensor data acquisition terminal, and the sensor structure frame diagram is obtained. Finally, six groups of experiments were carried out, 30 times in each group, and the sensor was used to identify the process of hand-made teaching. The number of successful experiments in the 6 groups was 26, 25, 28, 27, 29, and 27, respectively.

1. Introduction

Body movement is a visual language with rich expressiveness and meaning. We can understand a person's mental state and the content of expressions through human facial expressions, actions and actions, but it is much more difficult for computers. In order to use a computer to identify the information of human movement, first of all, it is necessary to collect the data of human movement with sensors, and then use the data of human movement to calculate and process with algorithms, and finally obtain recognition and obtain highly complex and informative movement data.

By researching and using more manual resources, teachers can have more material choices, allowing children to explore more topics, give full play to their creativity, and enrich their textbooks. Replacing kindergarten teachers and high school parents who do not fully understand hand-made,

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updating their knowledge and let hand-made work. The development of scientific evaluation standards can provide a background for kindergartens, a better understanding of children's handcrafting, and provide a background for a clear leadership role.

For multi-sensor, related scientists have made the following research.Xue JR provides a multisensory fusion framework aimed at understanding an autonomous transport environment. The frame uses geometric and semantic boundaries to seamlessly combine camera, data and GIS data to identify and sense obstacles effectively. Discuss the powerful mechanical visualization algorithm successfully integrated into the frame. Access multiple layers of mechanical visualization technology, from data collection to efficient processing of sensor data, to export low-level features, to design advanced objects and environments. The frame he proposed has been extensively tested on robotic machines, for eight years on real city scenes in its design[1]. The main objective of the SeabergTM study is to explore the capabilities and capabilities of a multisensor system consisting of heart rate sensors, Global Navigation Satellite System (GNSS) data and seven IMUs located at different locations. from the body. Used for outdoor skiing, and uses rigorous evaluation rules based on hand-to-foot ratios to determine the effectiveness of individual techniques in classic cross-country skiing. This is the first study to examine individual ski technologies and link them to GNSS data, which has identified and associated sub-technologies with different landscapes. This type of information helps skiers understand the technical and tactical aspects of daily training and races and provides tools for coaches and athletes[2]. Damage and damage should be detected as soon as possible in order to reduce operating and maintenance costs and extend the life of rotating machines. The detection capabilities of an infrared thermal imaging system, like any sensor-based system, are limited to the ranges detected by a single sensor. Janssens O proposed a multisensing system that not only uses thermal camera data with infrared images, but also uses vibration measurements to automatically position and detect the failure of rotating equipment. The results suggest that by combining these two types of sensor data, multiple conditions/errors and combinations can be determined more accurately by examining the flow rate of a single sensor[3]. In a recent article, Subedi S proposed a new method of detecting multiple MTT sensors in rare cases. The technology is developing a repetitive feedback mechanism, so a unique team recovery algorithm also benefits from knowing the target dynamics. Therefore, it is important to compare monitoring of these methods with the performance of the best resolution for multiple MTT sensors, whether or not they take into account missing samples. During the study, Subedi S analyzed and evaluated the Cramer–Rao efficiency limits of these two less complex MTT algorithms. And if the measurement vector is eliminated with missing samples and extra noise, the retrospective training system has been shown to outperform the traditional method[4]. Xing Z is concerned with Distributed Calm Filter Synthesis (DFKFF) where many unreliable network systems (MUNS) experience disproportionate interference. He proposed the optimal DFKFF algorithm for buffered MUNS and proved that it was compatible with the centralized optimal Kalman filter (COKFF) synthesis algorithm for buffered MUNS. Based on the optimal local Kalman filter with limited length buffer in each subsystem, he proposed a suboptimal MUNS DFKFF algorithm with limited length buffer. Compared to the COKFF algorithm of the MUNS buffer, the recommended DFKFF algorithm of the MUNS buffer is more robust[5]. Zhang L. proposed a new type of intelligent method for the detection of spherical screw degeneration based on deep mesh (DBN) fusion data and multiple sensors. Uses the Latin method to calculate the frequency spectrum of the original signal and calculates the frequency spectrum of the connection by combining data from multiple sensors. It uses an integrated database to create in-depth cognitive models based on studies that can automatically assess degeneration. He proposed the optimal DFKFF algorithm for unrelated MUNS and proved that it was compatible with the optimal central Kalman filter melting algorithm for unconnected MUNS. Compared to the MUNS COKFF buffer algorithm, the MUNS DFKFF buffer algorithm has a higher tolerance for errors[6]. Zhao X proposed multi-touch signal error diagnostics and Key Component Analysis (PCA) method to improve FCS performance. Using this method, it analyzes the correlation between the signals of different sensors based on the signals of several sensors and obtains simplified statistics for diagnosing errors based on PCA. Electronic monitoring of the operating status of the FCS, which can diagnose sensor and system level faults. Experimental results show that two typical error scenarios can be successfully diagnosed and differentiated, namely sensory error and critical system error. When a single sensor fails, the fuel cell immediately restores the sensor signal to ensure normal operation of the vehicle[7]. These methods have provided some references for research, but due to the short time and small sample size of the relevant research, the research has not been recognized by the public.

The innovation of this article lies in the introduction of sensor technology and data fusion technology to recognize the body movements of hand-made teaching, and obtain the overall structure block diagram of the body movement data collection system. The body language of a person is divided into dynamic language and static language, and a schematic diagram of action classification is obtained. It is proposed that the body movement recognition system for hand-made teaching is mainly composed of two parts: the data collection terminal and the data processing terminal.

2. Multi-sensor Data Fusion Manual Production Method

2.1. Pre-school Education

Early childhood education is an experimental activity that can encourage children (from birth to elementary school age) to learn and promote their all-round development. It is divided into preschool social education and preschool family education. Pre-school education can be divided into two types: broad sense and narrow sense. Pre-school education is one of the occupations with a high level of employment, and most kindergartens need to be booked [8]. Because the society lacks kindergarten teachers, and lacks kindergarten teachers with high education and quality. Such teachers must not only have a certain amount of practical artistic ability, but also must have comprehensive cultural education and human knowledge, extensive scientific research and good scientific research capabilities. Early childhood is an important stage of personal development. Therefore, preschool education plays an important role in the development of children. Data related to preschool education is shown in Figure 1.

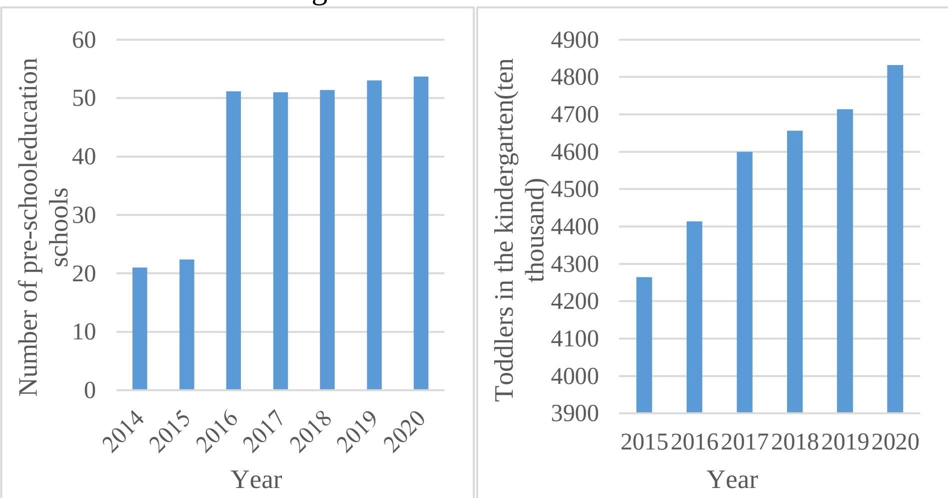

Figure 1. Pre-school education related data

Preschool education safety management refers to the management of the safety of children at the stage of preschool education. Early childhood is the budding period of life and a key link in human growth and development. Many things are learned at this stage. Therefore, we must pay special attention to the safety of pre-school education and carefully manage it. The scope of preschool education safety is too wide, mainly including environmental safety management, food safety management, and personnel quality safety management [9].

A total of 70 pre-school education interns in 10 kindergartens were comprehensively evaluated, and the results are shown in Table 1.

Table 1. Comprehensive evaluation form for intern open class

Evaluation standard	Excellent	Good	Qualified	Unqualified
Teaching objectives	15	24	29	2
Teaching content	12	33	22	3
Teaching structure	16	26	26	2
Teaching method	15	27	26	2
Classroom atmosphere	18	23	27	2
Lesson plan preparation	20	27	22	1

2.2. Sensor

The sensor is a detector. It can obtain measurement data and convert it into electrical signals or other forms of data output for data transmission, processing, storage and display on specific monitoring equipment. A sensor is a device or device that detects a fixed scale and can convert it into a signal that can be used for transmission according to a certain rule. The converted one can facilitate measurement. Normally, it is electricity. There are many forms of electricity, such as current, voltage, capacitance, etc. Generally, different output electricity forms are selected according to different situations [10].

The sensor element is used for direct contact with the measuring instrument, and the initial conversion includes converting the sensor element into a uniform amount of electricity used to measure quality perception. The sensor usually has a signal amplification circuit, because the electrical signal sent by the sensor is relatively weak and difficult to measure [11]. The sensor block diagram is shown in Figure 2.

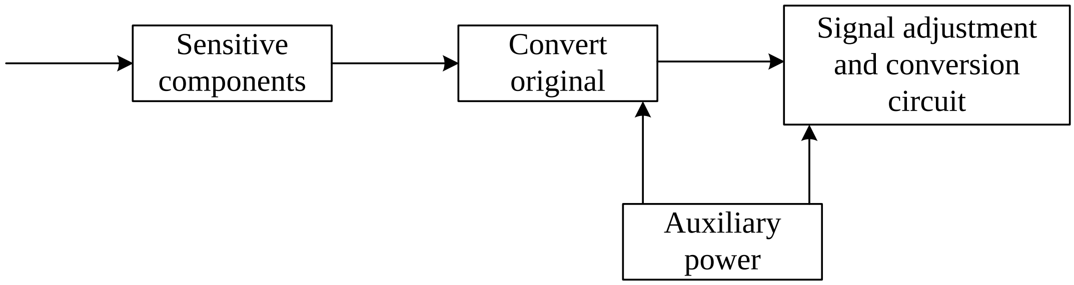

Figure 2. Sensor composition block diagram

The sensor is closely related to the detection technology, which is the window through which the sensor obtains the measurement. The sensor is located at the interface between the measured object and the detection system. This shows the importance of detection technology, so it is necessary to understand and master the detection technology in order to better use the sensor. The main task of detection technology is measurement. To obtain a series of data of the research object requires measurement. Only through measurement can a quantitative result be obtained. Measurement is the determination of the measured value, that is, the behavior of comparing the measured value with a standard quantity of the same nature to determine the multiple of the measured value relative to the standard quantity [12]. The measurement can be expressed by the following Formula:

$$x = op \tag{1}$$

$$Q(i,j) = \begin{cases} 1, d(i,j) \le r_s \\ 0, other \end{cases} \tag{2}$$

$$p(s,t) \begin{cases} 1, d(s,t) \le r_s - r_e \\ e^{-\alpha \times dist^{\lambda}}, r_s - r_e < d(s,t) \le r_s + r_e \\ 0, d(s,t) > r_s + r_e \end{cases} \tag{3}$$

$$WD = \sum_{i=1,\ldots,N}^{\overset{U}{i=1,\ldots,N}} A_i \tag{4}$$

x —Measured value

p —Standard value, the unit of measurement

o -multiple

The basic block diagram of the detection system is shown in Figure 3:

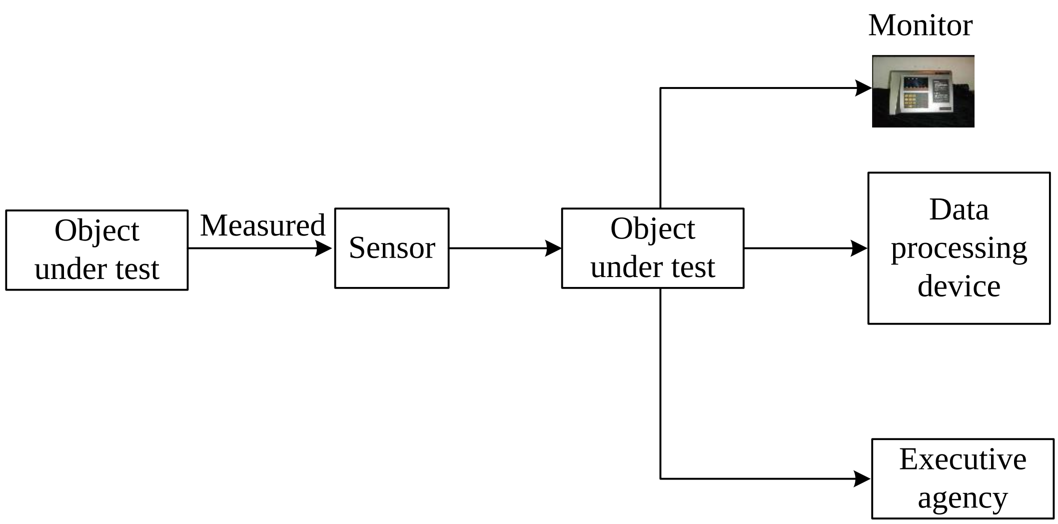

Figure 3. Basic block diagram of automatic detection system

For the measurement system, it can be divided into an open-loop measurement system and a closed-loop measurement system [13]. The direction of information transformation in an open-loop system is in one direction, and the input and output relationships are as follows:

$$y = m_1 m_2 m_3 x \tag{5}$$

$$K_a = \sum_{1}^{N} K_i ; K_i = \begin{cases} 0, a \in a_i \\ 1, a \cap a_i \ne a \end{cases} \tag{6}$$

$$R_{Tx} = k \times R_{elec} + k\alpha_{fs} d^2, d < d_0 \quad (7)$$

$$R_{TX} = kR_{elec} + k\alpha_{mp} d^4, d > d_0 \quad (8)$$

For a closed-loop system, one is the positive channel, and the other is the feedback channel [14]. The input and output relationship is as follows:

$$y = \frac{m_1 m_2}{1 + m\chi} x \approx \frac{m_1}{\beta} x \quad (9)$$

$$f(x) = \frac{1}{\pi\alpha} \exp\left(-\frac{x^2}{2\alpha^2}\right) \quad (10)$$

$$t(r,\theta) = \iint f(r,\theta) drd\theta \quad (11)$$

$$Z_c \geq EF = \begin{Bmatrix} 0, \omega = \pi/2 \\ 2Z_s \cos\omega, 0 < \omega < \pi/2 \\ 2Z_s \omega = 0 \end{Bmatrix} \quad (12)$$

$m = m_2 m_3$

β —Feedback coefficient

Since the closed-loop measurement system has a feedback link, measurement errors can be reduced, even without measurement errors [15]. Its system block Figure 4 is as shown.

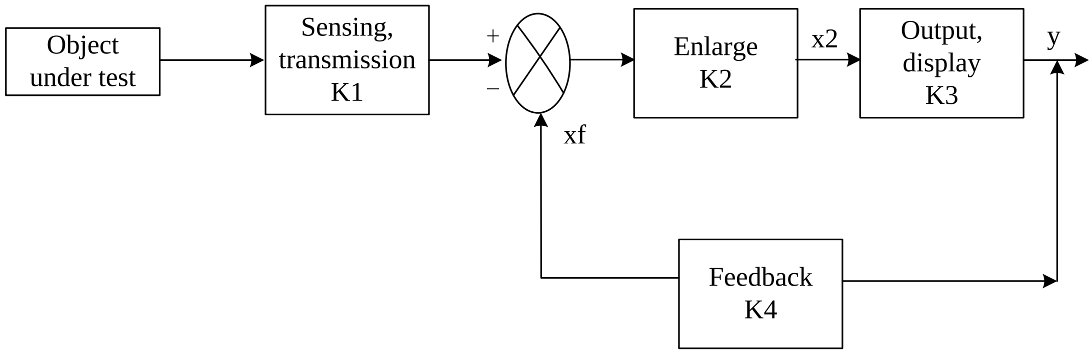

Figure 4. Block diagram of closed-loop measurement system

For the static characteristics of the sensor: when the input signal is stationary, the relationship between the sensor output and input does not change over time[16]. That is, the result can be represented by an eternal formula. Input x and output y can be represented by the following formula:

$$y = n_0 + n_1 x + n_2 x^2 + \Lambda + n_i x^i \quad (13)$$

$$T_L(r,\theta) = 1 - \exp\left(-\frac{(2r\cos\theta/L)^2}{2\rho^2}\right) \quad (14)$$

$$n_L \geq \begin{pmatrix} \lg(1-o) \\ \lg[1-p_{ol}(r,\theta)] \end{pmatrix} \tag{15}$$

The static characteristics of the sensor can be expressed by a series of indicators, such as sensitivity, linearity, repeatability, hysteresis and drift, and so on.

Linearity: Linearity refers to the degree of linearity between the input and output of the sensor. The current levels are linear and non-linear. In the actual measurement, we hope that the sensor has linear characteristics, so that it is convenient for us to measure, and it can also reduce the measurement error. However, because many uncertain factors are often encountered in actual measurement, it is said that the sensor maintains linear characteristics, but linear compensation is often performed, so that the sensor maintains linear characteristics as much as possible [17]. The linearity of the sensor can be expressed by the following Formula:

$$\alpha_L = \pm \frac{\Delta L_{\max}}{Y_{FS}} \times 100\% \tag{16}$$

$\Delta L_{\max}$ —Absolute error of maximum nonlinearity

Y_{FS} —The output value of the full scale of the sensor

Sensitivity: The sensitivity of the sensor refers to the reciprocal of the ratio of the change in output Δy caused by the change in input Δx of the sensor. It can be expressed by the following Formula:

$$Q = \frac{\Delta y}{\Delta x} \tag{17}$$

—Sensitivity of the sensor

Hysteresis: Hysteresis refers to the phenomenon that the curves do not coincide when the input amount increases and when the input amount decreases [18]. For the same input signal, the output is different from large to small and small to large. The difference between the two is called the hysteresis difference, expressed by $\Delta Z_{\max}$, and the hysteresis error is expressed by the following Formula:

$$\alpha_H = \frac{\Delta Z_{\max}}{Y_{FS}} \times 100\% \tag{18}$$

$\Delta Z_{\max}$ —Absolute error of maximum nonlinearity

Drift: Drift refers to the constant input, but with the passage of time, the output will change. The reason for this is, on the one hand, the change in the sensor's own structure, and on the other hand, the change in the surrounding environment during measurement, such as the temperature and humidity of the surrounding environment. The temperature drift is generally expressed by the following Formula:

$$R = \frac{y_t - y_{20}}{Y_{FS} \cdot \Delta t} \times 100\% \tag{19}$$

The dynamic Formula of the sensor is as follows:

$$c_n \frac{d^n y}{dt_n} + c_{n-1} \frac{d^{n-1} y}{dt^{n-1}} + \Lambda + c_1 \frac{dy}{dt} + c_0 y = o_m \frac{d^m y}{dt^m} + o_{m-1} \frac{d^{m-1} y}{dt^{m-1}} + \Lambda + o_1 \frac{dy}{dt} + o_0 x \tag{20}$$

Object detection sensors, objects and observers constitute the three elements of a wireless sensor network. In wireless sensor networks, wireless sensor nodes transmit the collected tracking data in a multi-band manner. The data observed during transmission can be processed multiple times by multiple nodes, finally at the synchronization node, and then to the remote transmission medium (Internet, satellite, microwave, glass fiber, etc.). The control node configures the network according to the received data, performs monitoring tasks, and collects monitoring data.

Wireless sensor networks have a wide range of functions. In order to obtain information quickly and effectively, multiple touch nodes are usually set in the monitoring area. Therefore, the general characteristics of WSN basically have two aspects: on the one hand, large coverage and large geographic area. The second aspect involves the placement of a large number of sensor nodes. The dense placement involves placing a large number of sensor nodes in a small on-site observation area [19].

Wireless sensor networks have the following advantages: (1) A large number of nodes can expand the coverage of the monitoring area and reduce inanimate points or holes. (2) Large-scale node placement enables wireless sensor networks to achieve high signal-to-noise ratios at different angles, thereby increasing system redundancy and overall network resistance. (3) Distributed data processing and collection methods can enhance the processing capabilities of wireless sensor networks, thereby improving monitoring accuracy and reducing the performance requirements of sensor nodes [20].

3. Multi-sensor Data Fusion Hand-made Experiment

Pre-school education is a foreshadowing stage of primary education and an important part of China's school system. It should be noted that the pre-school education in this article includes all public and private parks, but does not include specialty training institutions, such as music, art, dance and other training institutions.

Preschool education safety management refers to the management of the safety of children in the preschool education stage. Infancy is the budding period of life and is a key link in human growth and development. Many things are learned at this stage. Therefore, we must pay special attention to the safety of pre-school education and carefully manage it. Preschool education safety mainly includes three aspects: environmental safety management, food safety management, and personnel quality safety management.

Pre-school hands-on education is an integral part of pre-school art education and an important part of pre-school education. Modern physiology shows that the human brain is divided into left and right hemispheres.The left hemisphere controls human language and abstract ability, while the right hemisphere controls general intuitive understanding, imaginative thinking ability, characteristics, etc. This is because proper brain development is important to the individual, and it is essential to personal success. The goal of Chinese education is to develop human potential. The left hemisphere looks more developed, while the right hemisphere looks weaker. We all know that the left and right hemispheres of the brain control the left and right of the human body. The left hand ability can train the right hemisphere and the right left hemisphere. Handicraft is an exercise of putting hands together, which helps to develop a general brain, helps children learn creatively, and promotes the healthy development of various fields.

In order to understand the real situation of manual labor teaching for children aged 5-6 years old, some manual classes in the older kindergarten classes are selected for learning and research. While the development of handcraft activities has been improved, there are still many challenges in handcraft teaching.

The effective implementation of the educational activity process depends on the teacher's appropriate teaching methods to achieve. In teaching, not only the teacher's "teaching" process, but also the student's "learning" process. Together they constitute the activity process. In the entire link of the activity, the teacher uses the method to design and manage it, so the teacher's teaching method has a key influence on the layout and execution of the activity process. Imitation is the nature of young children, and young children often learn through imitation, so most teachers take the form of demonstration when performing manual activities. The model law can enable children to better watch and understand the difficult and easy parts of the teacher in the demonstration, so that children can imitate it. However, in the case analysis, it is found that some teachers' demonstrative teaching in manual activities is too much, and they are all dominated by teachers, which leads to insufficient expression of children's subjectivity. In the process of some manual activities, the teaching method is still based on teachers and children as supplementary. Almost the entire process is controlled and led by the teacher, and children's autonomous learning rarely even curbs their need for creativity. Therefore, in some manual activities, children are just "tools" for teachers to teach, in order to smoothly complete the class, and completely ignore the children's subjectivity. For example, the process of the artist "Little Bean Animal" in a large class is: (1) The teacher shows an example of a giraffe made up of beans and toothpicks to demonstrate the operation process. (2) It shows examples of turtles, chickens, etc., and hang a picture of a zoo consisting of beans and toothpicks on the blackboard. (3) Children learn to make "small bean animals". As a result of the operation, except for one child who made a turtle, the rest of the class made a giraffe. When the teacher conducts this class, he starts with a demonstration and ends with an example. The children just imitate the function of the operation, and the autonomy cannot be brought into full play.

According to the difference in the abstract level of target data in the fusion system, sensor data fusion can be divided into two levels: data-level fusion and decision-level fusion. Figure 5 is a schematic diagram of the two data fusion structures.

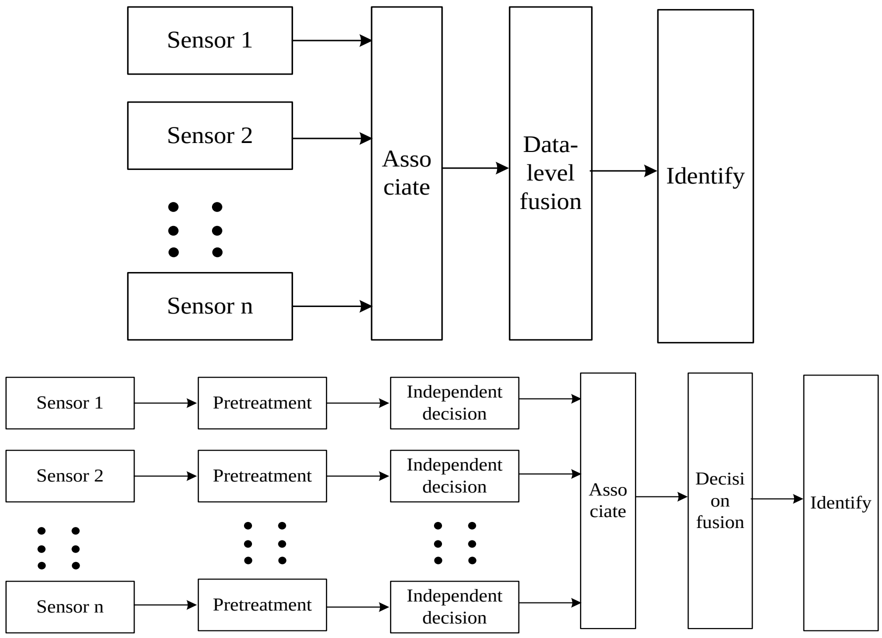

Figure 5. Schematic diagram of fusion structure

When a person communicates with a computer, about 93% of the information is transmitted through non-verbal, mainly body language. The movement of hands and feet can be described as various movements, postures and movements of the human body, head and limbs to express thoughts or achieve goals. The action classification is shown in Figure 6. It mainly involves the torso movement of the chest and abdomen, with the original arrow as the central axis. Head movement refers to head rotation and facial movement. The movement of the upper limbs is mainly related to the movements and postures of the hands and wrists. The movement of the lower limbs is the walking, running and jumping of the human body. According to the level of movement, body movement is divided into complex movement and joint movement. It is easier to distinguish detailed movements such as gestures and facial expressions of the upper and lower limbs and general movements such as body movements.

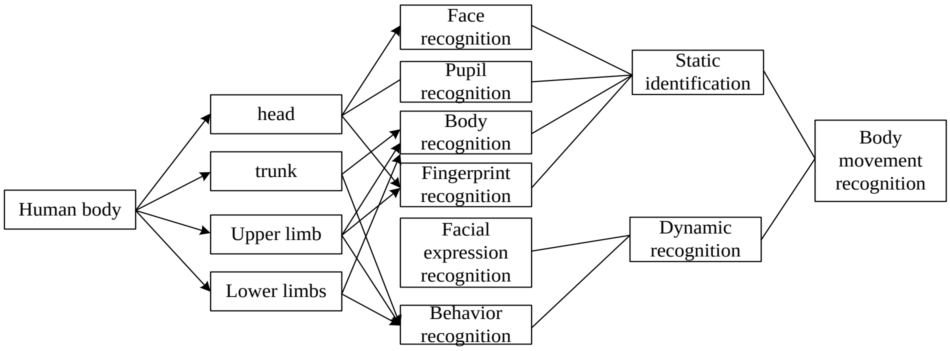

Figure 6. Body movements and recognition classification

The inertial sensors used in this article are acceleration sensors and gyroscopes, and the equivalent inertial output devices are acceleration and angular velocity. The magnetic sensor is a sensor with magnetoresistance effect, and the output is the force of the magnetic field. The image sensor is a Kinect sensor, and the output is color image, image depth and bone information. The data receiving terminal is designed based on inertial sensors, magnetic sensors and image sensors, and its structural block diagram is shown in Figure 7.

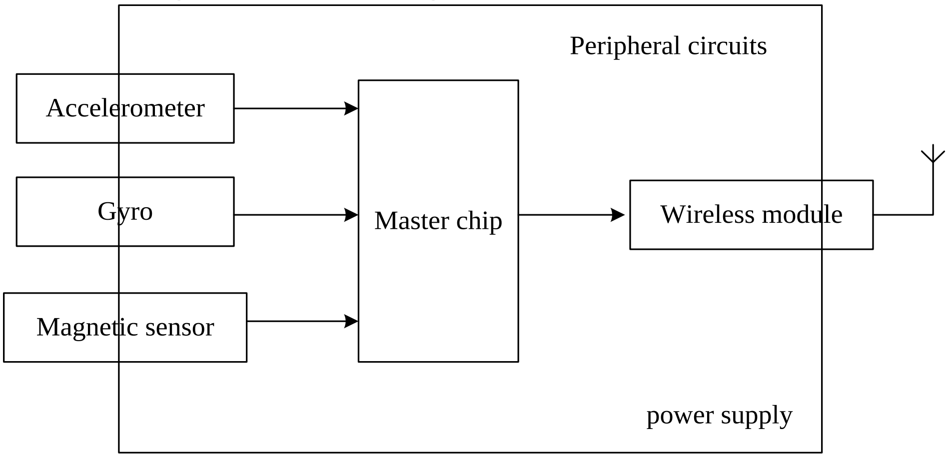

Figure 7. Block diagram of data acquisition end

The overall structure diagram of the body movement data acquisition system is shown in Figure 8. The multi-sensor collection terminal can be used as a child node or as a parent node. When it is a parent node, the sensor collection function is turned off, and the polling method is used to collect data from each child node. When a set of data is collected, it is uploaded to the data processing terminal through the wireless module.

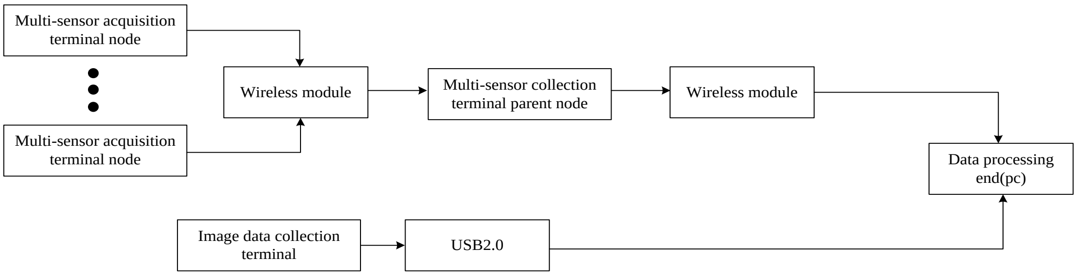

Figure 8. Block diagram of the body movement data acquisition system

The multi-sensor data acquisition terminal has been improved for the selection of magnetic sensors and is divided into two versions to achieve size reduction and power consumption. The overall structure of the two versions is basically the same, mainly including the power supply circuit, the main control chip, acceleration and angular velocity sensors, magnetic sensors and radio frequency modules. The block diagram is shown in Figure 9.

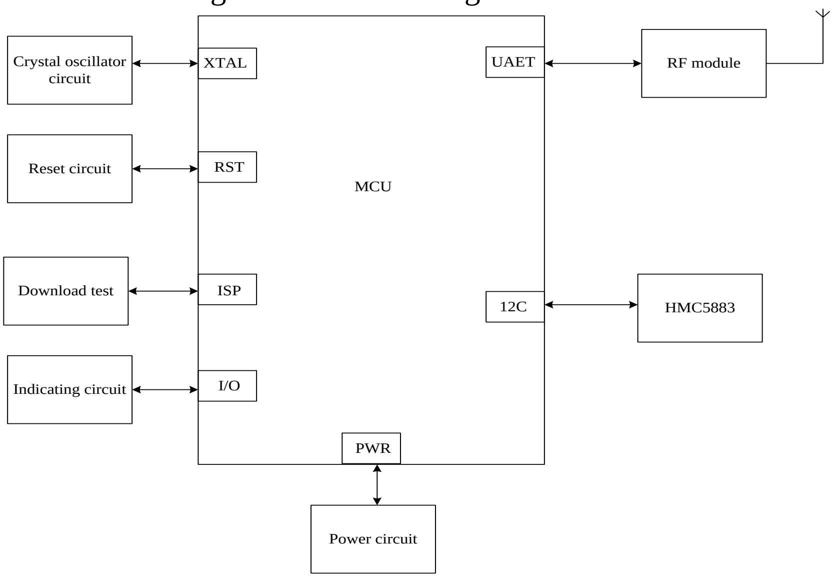

Figure 9. Block diagram of data acquisition end

Because the motion data requires high real-time performance, in the processing of inertial data, in addition to threshold filtering and selecting the range according to the actual situation, the high sampling rate of the sensor is also used for average filtering. The important registers are shown in Table 2 and Table 3.

Table 2. MPU6050 register configuration

Register name	Register address	Instruction
SLAVEADDRESS2	0x3c	Register operation address
CONFIG_A	0x00	Selection of sampling times and output rate
CONFIG_B	0x01	Range selection
MODE	0x02	Measurement mode selection
DATA_X	0x03 0x04	X-axis magnetic field data
DATA_Y	0x07 0x08	Y-axis magnetic field data

Table 1. MPU6050 register configuration

Register name	Register address	Instruction
SLAVEADDRESS1	0xd0	Register operation address
SMPLRT_DIV	0x19	Sample rate divider
PWR_MGMT	0x6d	Power management and clock configuration
CONFIG	0x1a	Low-pass filter configuration
GYRO_CONFIG	0x1b	Gyro self-test and range selection
ACCEL_GONFI	0x1c	Accelerometer self-test and range selection

The child node acquisition command is sent by the parent node to all child nodes, and the format of the data frame is as follows. The child node data preparation query command is sent from the parent node to the child node in turn, as shown in Table 4:

Table 4. Sub-node data frame format

	Frame header	Target node	Source node	Logo	End of frame
Number of bytes	2	1	1	1	2
Example	55 AA	OF	10	01	AA 55
Number of bytes	2	1	1	3	2
Example	55 AA	10	01	03	AA 55
Number of bytes	2	1	1	3	2
Example	55 AA	OF	05	05	4A

Use the sensor to identify the manual teaching process, extract the bone information, select 30, 50, 70, 90, 100, 200 for the number of acquisition frames, and average 10 times for each frame. Take 6 groups of experiments, each group has 30 times to recognize the mechanical energy of the hand-made teaching process. The experimental results are shown in Figure 10. The left picture is the average starting frame picture, and the right picture is the number of successful identifications.

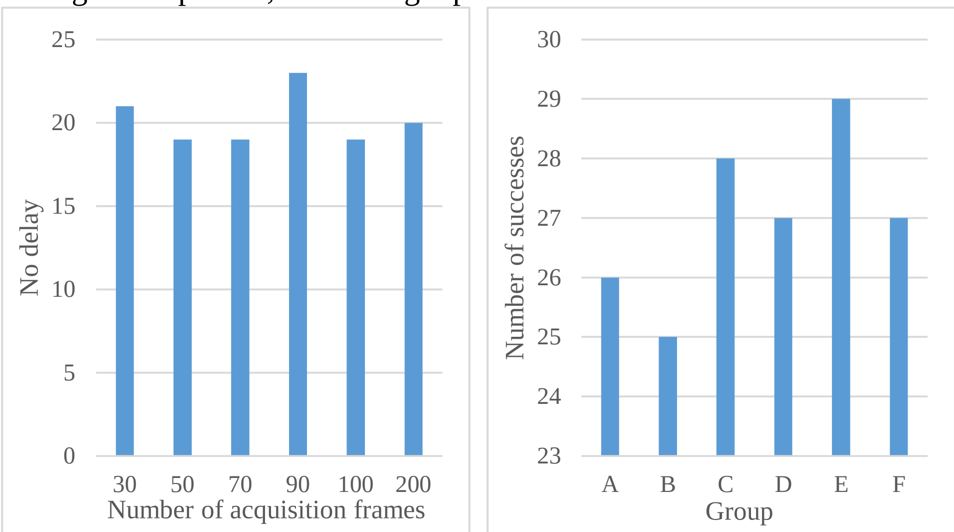

Figure 10. Experimental result

4. Discussion

Static perception refers to the human body's perception of all or part of the information in a static state, such as state perception, facial perception, fingerprint perception, pupil perception and so on.

State recognition means recognizing certain gestures. The face, fingerprints and pupils are mainly used for identification. The fixed detection is kept at a constant time, and the recognition result is obtained by comparing the information collected by the sensor with the known data model.

Dynamic cognition refers to the recognition of all or part of the motion information of the human body during the movement, such as recognizing behavior, recognizing the number of steps, recognizing facial expressions, recognizing gestures, etc. These include behavioral cognition, mainly knowledge of general body movement, such as gymnastic movement recognition. Footprint detection is based on the movement of the lower limbs. Face recognition is based on images to detect changes in the face. Gesture detection is usually used to convey meaning and emotion, and control is mainly based on the trajectory of hand and finger movement.

The source of children’s educational needs is unknown. It may be the motivation of the child, or it may be perceived by various people in the later development process. The most basic and basic requirements for kindergarten children are the needs of love and self-esteem, which are the foundation of all children's activities. If children do not feel the love of their teachers and leaders, or if they feel that they are bad and lose confidence in themselves, they will have no positive motivation to achieve better goals. Therefore, in practical training, teachers should focus on the various needs of children and encourage positive teaching behaviors, so as to stimulate students' interest, eradicate children's intrinsic learning motivation, and have a positive impact on students.

5. Conclusion

Children's manual activities are part of children's art education, which can cultivate children's practical ability and aesthetic ability, and stimulate and develop children's creative thinking. It can learn in action, learn in learning, have fun and enjoyment at the same time, and get the harmonious development of body and mind. This is why children's manual activities occupy an important position in early childhood education. In this paper, sensor technology is introduced to recognize and record the process of making Aoxue with hands and feet, so as to increase the variety of methods for children to learn to make by hand. This article starts a preliminary forecasting study. In view of the limited data sources and academic level, there are unavoidable omissions in the study. The analysis of the status quo analysis stage is not thorough enough, only showing the changes of relevant indicators, and lacking internal judgment and analysis. At the stage of theoretical research, this article does not have a thorough grasp of the theory. Although the body movement data acquisition system designed in this paper can effectively collect movement data, there are still many areas worthy of improvement and perfection in the hardware and software of the acquisition system. For example, the size of the multi-sensor data collection terminal is reduced while maintaining the collection rate and low power consumption, so that it is more suitable for body wear.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

Reference

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