Hindawi
Mobile Information Systems
Volume 2023, Article ID 9830407, 1 page
https://doi.org/10.1155/2023/9830407

Retraction

Retracted: Walking Position Data in Football Training Based on Embedded Action Recognition System

Mobile Information Systems

Received 1 August 2023; Accepted 1 August 2023; Published 2 August 2023

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] L. Li, "Walking Position Data in Football Training Based on Embedded Action Recognition System," *Mobile Information Systems*, vol. 2022, Article ID 4094025, 13 pages, 2022.

Hindawi
Mobile Information Systems
Volume 2022, Article ID 4094025, 13 pages
https://doi.org/10.1155/2022/4094025

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Research Article

Walking Position Data in Football Training Based on Embedded Action Recognition System

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Received 16 March 2022; Revised 26 April 2022; Accepted 23 May 2022; Published 22 June 2022

Academic Editor: Liming Chen

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With the development of image recognition and pattern recognition, action recognition has become a hot research direction in the field of computer actions. Because the embedded platform has the advantages of small size and low power consumption, it is a good choice to use the embedded platform for action recognition. These sensor data are used to overcome the drift error of the gyroscope when the positioning data are collected, and the accuracy and reliability of the data are improved. The system uses two data forwarding nodes to aggregate the data of each sensor and then transmit it to the host computer. The data aggregation node can communicate and upload data by means of Bluetooth or wire. In order to deeply study the relevance of the embedded action recognition system in collecting football training positioning data, this paper uses simulation model establishment method, data collection method, and theory and practice combination method to collect samples, analyzes the embedded action recognition system, and streamlines the algorithm. Using computer technology as a support when building a simulation model, the first thing you need to have is a certain computer technology because when building a simulation model, not all objects can be modeled. At this time, only computer technology can be used as a support to build a simulation model of some objects and create an action recognition system that can record the position data in football training. After establishing the human body simulation recognition model, use MATLAB to extract the K bone information. When collecting, the human body is facing the K device, the number of acquisition frames is 25, 55, 75, 95, 105, and 205, and each frame number is collected 10 times. Take the average. The delay time is 4s. The result shows that the 20 key bone point outputs by K come from the RGB camera on the same side. Further study the actual utility of the compensated model in the presence of occlusion. They are worn on the middle of the thigh and calf, respectively. In a sensor, the measured value of thigh length L1 is 0.6 m, and the value of calf length L2 is 0.4 m. Take the right knee as an example. When the leg is raised, the b-axis coordinate increases by 2%, and the c-axis coordinate decreases by 1.8%. When the leg is lowered, the opposite is true. It can be seen that the compensated coordinate is consistent with the action. It is basically realized that starting from the embedded action recognition system, a model that can support the analysis of football positioning data is designed.

1. Introduction

With the rapid innovation of football skills and tactics, the confrontation on the football field has intensified, and the offensive and defensive transitions have accelerated. Athletes have to do running, sprinting, emergency stop, jumping, and physical confrontation on nearly 8000 square meters of field for more than 90 minutes, and complete a series of technical actions in the fierce competition. The walking position data are the athlete's ability to react, dodge, and judge quickly, and the lower limb braking ability is the athlete's rapid deceleration and braking. In recent years, with the fierce development of football, football training for youth is also blooming everywhere. Junior high school students are in the golden period of physical development and the best period of football technology development. Physical education teachers and coaches should seize this best development period to fully develop their physical qualities such as strength, speed, agility, flexibility, and coordination [1]. The football technical and tactical training process is the process of reshaping and forming the team's technical and tactical play and characteristics. The complexity and variability of this process and the variety of influencing factors determine the multiple possibilities for the development space of the team's technical and tactical play.

With the rapid development and spread of technology, how to make computers execute instructions issued by people faster and more accurately is a hot topic in this field. Human conversations have gradually evolved from traditional transmissions such as computers and strokes to new and faster interaction modes such as letters and bodies. To use a computer to diagnose human body language, first use sensors to collect human motion data, then add, subtract, multiply, and divide the human motion data through a series of algorithms, and finally realize the differentiation of targeted concepts of high-difficulty and high-content motions. The effective recognition of a casual small action has great difficulty in recognition, and the promotion of this related skill can greatly promote the depth of human beings in sports and other fields. Movement is a major research topic in the field of humans and machines, and the design of a flexible and comprehensive body movement library is a decisive factor in completing body language recognition.

Football is one of the most popular sports in the world. People have never given up data analysis of their movement and used various advanced technologies to achieve this goal. In 2019, *G* proposed a compact motion descriptor to describe the adjacent trajectory pattern of human action recognition. The proposed method introduces a strategy that models the local distribution of neighboring points by defining a process of spatial points around the motion trajectory. In particular, a two-level occurrence analysis was carried out to discover the movement pattern represented by the track points. First, calculate the locally occurring words on a circular grid layout centered on a fixed position of each track. Then, the regional occurrence description is realized by expressing the action as the most frequently occurring local word in a specific video. The second generation layer can be calculated for the entire video or each frame to achieve online recognition. This compact descriptor, with a local size of 72 and a sequence descriptor size of 400, is of great significance in real-time applications and environments with hardware limitations. The strategy he proposed was evaluated on the KTH and Weizmann data sets, and the average accuracy rates were 91.2% and 78%, respectively. In addition, by using only the first 25% of the video sequence, further online recognition was performed on UT interaction, achieving an accuracy of 67%. Although the modeling process is perfect, it is a pity that the accuracy of the algorithm is not high, and there is nothing to say [2]. In 2016, Qin L researched the positioning technology of the system to help drivers make judgments and improve driving safety. Therefore, the system has broad application prospects. The research content of this article can enrich and supplement the PNL visual positioning method and has the significance of theoretical research. An improved method for vehicle license plate measurement based on monocular vision is proposed. This method combines the characteristics of fast analytical solution and high positioning accuracy of iterative solution, has high robustness, and overcomes the multi-solution problem of P3P iterative method. Simulation experiments show that compared with the P4L method, the positioning accuracy of the improved positioning method has been greatly improved. At the same time, the real-time performance of the collision avoidance warning system with improved visual positioning method has been greatly improved, and the new positioning algorithm has a good performance in real-time performance, which greatly improves the processing capacity of the system. Although the processing power of the system has been improved, it is ultimately a wrong research direction and cannot be applied to football [3]. In 2020, based on the characteristics of athletes, Ma B developed and designed a C/S mode athlete training process monitoring system based on mobile artificial intelligence terminal technology. It uses GPS to obtain real-time position information of athletes and provides real-time guidance for athletes. In order to reveal the changing laws of various indicators in the training state of athletes, Ma B conducts simultaneous tracking and analysis from the characteristics of individual athletes sports function, coach training plan arrangement, brain function status, conventional physiological and biochemical indicators, nutrition, etc. The 16 athletes were randomly divided into experimental group and control group according to men and women and events. The basic situation of the experimental group and the control group is roughly the same. Before the experiment, the indexes of the experimental group and the control group were statistically tested. The results show that there is no significant difference between the two, which is in line with statistics. However, there are errors in his experimental process and data recording errors [4].

The innovations of this article are as follows: (1) summarize the current status and application of body language at home and abroad by means of references, and analyze and study the determining conditions of body language in the field of human-computer interaction; (2) without external interference under the condition of using electromagnet to realize the measurement and marking of the ground, the data set is used to collect the actions of the football players, and the calibration values of the walking position in the process of walking to standing, rolling, and falling are analyzed; (3) the completion of the database of the embedded system is completed. According to the requirements of products and development, on the basis of the normal startup and operation of the system, innovate and streamline the file system as much as possible. Through the above work, the embedded action recognition system can be accurately applied to the movement analysis of the athlete's training data, and the recognition efficiency is guaranteed.

2. Implementation Method of Moving Position Data Analysis in Football Training Based on Embedded Action Recognition

2.1. Football Training. "Training" is a pedagogical term, which is similar to the meaning of teaching. The purpose of training is to enable trainees to acquire a behavior or skill. Please rephrase the sentence for clarity and correctness.". "Xun," "Shuowen" is defined as preaching, Congyan,

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Chuansheng [5]. "Training" in the sense of physical education refers to the planned and step-by-step mastery of certain skills through learning and counseling. It means that people consciously cause the trainees to have physiological reactions, such as building conditioned reflexes and strengthening muscles, thereby changing the training. The purpose of the activities of the quality and ability of the person is to cultivate and shape the person [6]. Dumping the ball: Do not hook up with your toes, and do not stand still under your feet. You can better adjust the center of gravity and control the ball when you move. Dribbling: Touch the ball as much as possible, preferably one step at a time. Stopping: Watch and move attention. Observe the situation of the incoming ball, quickly judge the landing point, and move in time. Shooting: It is roughly the same as passing the ball through the arch of the foot, but it increases the power and improves the accuracy.

Football is known as the "world's No. 1 sport" and is the most influential individual sport in the global sports world. With the summary of historical experience and the active orientation of national policies, the development of football mainly focuses on the concept of football training, youth football, campus football, football development model, football culture, etc.

To sum up, the research uses "football training" as the key word, and nearly 100 literature have been consulted in VIP. Scholars' research on training concepts is mostly based on the training concepts of different projects, the nature, and construction of training concepts. Today, when competitive sports are at its peak, the training concept urgently needs to cater to the international trend, combine the internal development law of the event, and innovate the training concept. In innovative training concept, the essence of innovation is the concept of reunification of subjective and objective in the process of sports training, which promotes the breakthrough and scientific development of the training concept of competitive sports with innovative thinking [7].

2.2. Data Analysis and Collection. In order for the network coordinator and network management to work properly, a high-performance controller needs to be selected. The high performance here has to do with the controllers used by end devices and routers in a Zigbee network. High performance and powerful processing power are important reference factors for the controller of the network coordinator. First consider the simplest case; that is, for the entire football field, a coordinator can cover the entire area. That is to say, all player points can be connected to the network created by co [8]. Players only need to wear segment points with sensors, and they can connect to the network normally in any corner of the field and transmit sensor data to co, which is responsible for identifying different terminal segment points and different types of sensor data. In the end, co will transmit the aggregated information with the identification of each athlete to the terminal through the serial port in real time for display [9]. On the contrary, the terminal can also send instructions to the co in real time, such as suspending the data transmission of a certain segment or speeding up the data transmission of a certain segment. But this method has a prerequisite; that is, the co must be able to support a large enough range; otherwise, for any segment of the football field, it may not find the network in a certain area and cause the system to malfunction. In order to make up for the shortcomings of this method, we can use the following improvement plan to increase the area covered by the router network in an increased way to reduce the pressure of co [10]. Figure 1 shows a structural simulation diagram of this improved method; with the development of the routing industry, router technology is constantly innovating and upgrading. From the first generation to the fifth generation, routing technology is moving toward intelligence step by step, and its role in the communication network is more important to achieve business flexibility and high-performance organic combination.

In Figure 1, it can be clearly seen that CO cannot cover the entire football field area, so we have added four routers around the field to increase the actual range of the network. As shown in the figure, each router can expand the range of the wireless network. In theory, four routers can be enough to cover the entire football field area, and the effective distance of each router only needs 55 meters. In this way, the terminal segment point on the field can find the nearby co or router at any position [11]. This structure is a complex topology.

2.3. Action Recognition. There are two main ways to obtain motion data: one is to use a black camera or other types of cameras to take pictures, and the other is to use an inertial sensor to cooperate with the equipment to collect the medium speed product and range speed change in the-process. More than 93% of the information in the process of people is transmitted by nonvoice, which is mainly by hands and feet. Hand and foot movements can generally be described as various forms and movements of the skeleton, head, and long bones in expressing people's attempts to pay attention or in the process. Movement classification is shown in Figure 2. Hand and foot movements can be divided into small movements and large movements according to the scale of movement. Small movements such as gestures and expressions, and large movements such as long bones and backbone movements are relatively easy to recognize [12]. In recent years, with the development of information technology and the popularization of intelligent technology, the global technological transformation is further advancing, and technologies such as cloud computing, Internet of Things, big data, and artificial intelligence are also developing rapidly. Among them, human motion recognition technology has begun to be used in computers widely used in vision-related fields.

As shown in picture 2, according to the difference in three-dimensional space and time, human hand and foot processing can be roughly divided into two categories: dynamic recognition and static recognition. Static recognition refers to the recognition of overall or partial information when the human body maintains a static posture,

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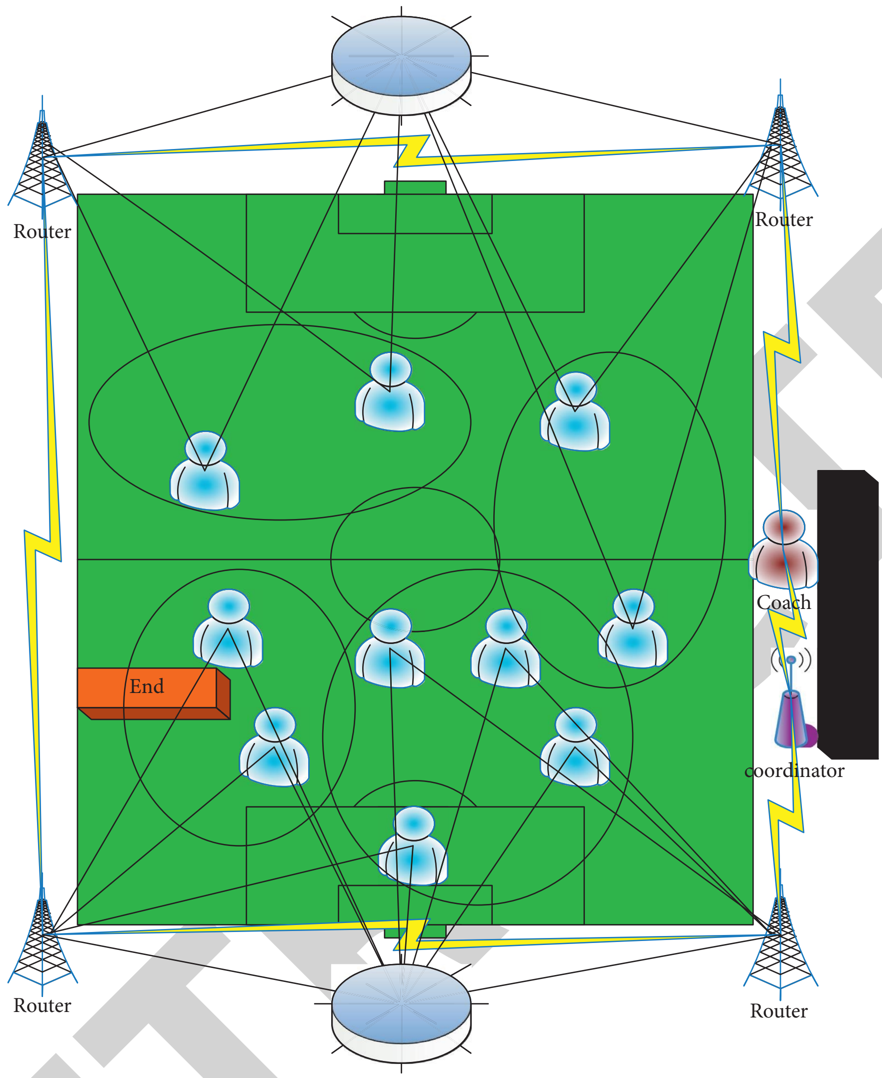

FIGURE 1: Improved model of data acquisition system.

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such as body shape recognition [13]. Motion recognition refers to the recognition of the overall or partial motion content of the human body, such as limbs, hands, and feet [14].

Suppose two time series are m and z, and their lengths are o and n, respectively, one is the reference template, the other is the test template, and the value in the sequence is the characteristic value of each frame [15].

$$\begin{aligned} m &= m_1, m_2, \ldots, m_o, \\ z &= z_1, z_2, \ldots, z_o. \end{aligned} \tag{1}$$

In order to pair the two sequences, first construct a distance matrix w of $o \times n$. The matrix element w (u, l) represents the distance between the two template elements m_u and z_l. Here, the Euclidean distance $w(u, l) = (m_u - z_l)^2$ is used; that is, the sequences m and z are single similarity between frames [16].

$$w = \begin{bmatrix} w(m_1, z_1) & w(m_2, z_2) & \cdots & w(m_1, z_n) \\ w(m_2, z_1) & w(m_2, z_2) & \cdots & w(m_2, z_n) \\ \vdots & \vdots & \ddots & \vdots \\ w(m_o, z_1) & w(m_o, z_2) & \cdots & w(m_o, z_n) \end{bmatrix}. \tag{2}$$

The process of dynamic regularization is to find a path with several points in the distance matrix, so that the sequence of points that the path passes through has the smallest Euclidean distance and the highest similarity [17]. Define the regular road as d, where the g th element $d_g = (u, l)$ represents the mapping relationship between the sequences m and z:

$$d = \{d_1, d_2, \ldots, d_g\}, \quad \min(n, o) \le g \le n + o - 1. \tag{3}$$

When the constraints are met, choose the path with the lowest cost from many roads:

$$wsd = \max\left\{ \frac{\sqrt{\sum_{g=1}^{g} d_g}}{g} \right\}. \tag{4}$$

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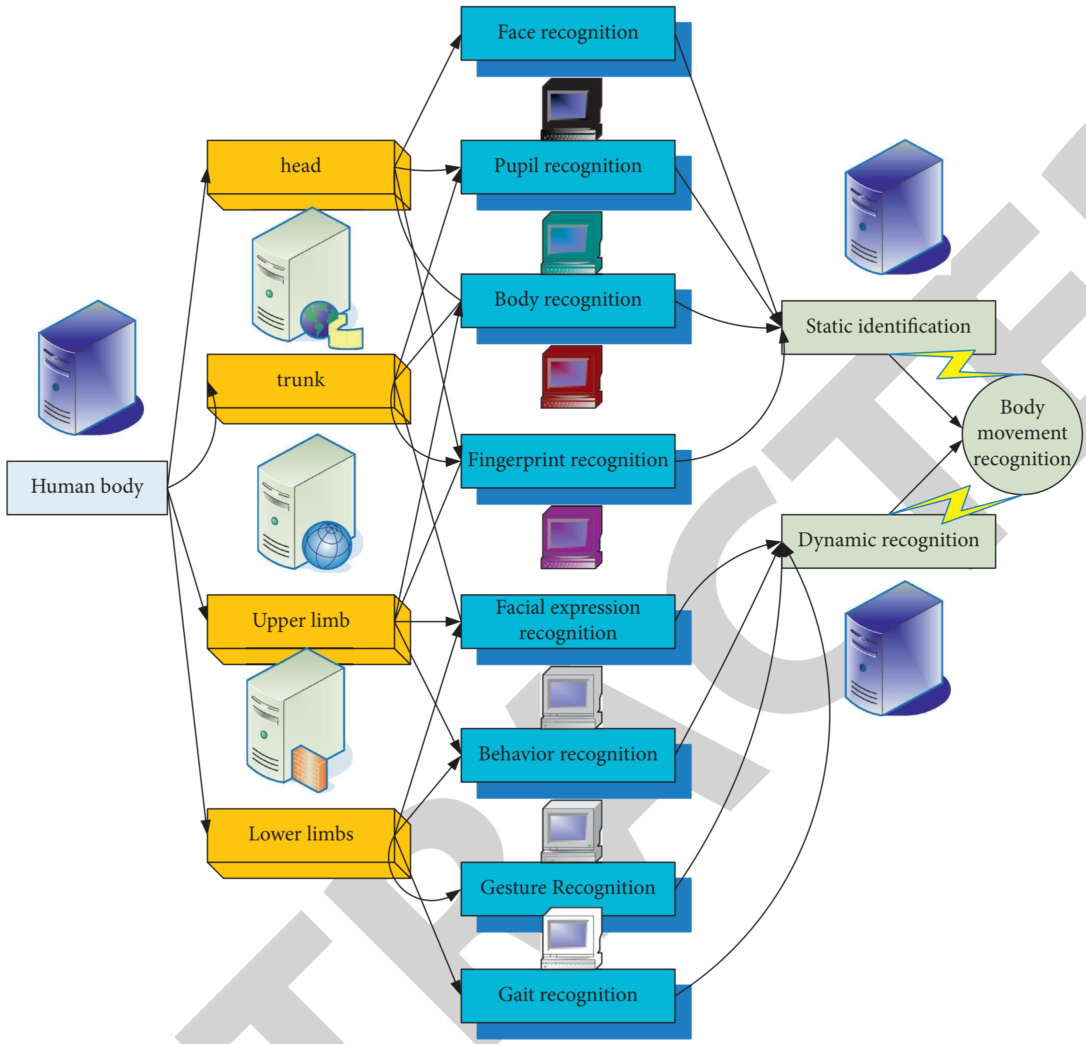

FIGURE 2: Body movement and recognition classification.

Among them, g is the path length corresponding to different paths [18].

The best distance is the road that minimizes the distance along the path, which can be easily determined according to the recognition algorithm. Define a cumulative distance $\alpha(u,l)$, as in (5). Match these two sequences m and z starting from the point (0, 0). When reaching a point, the distance calculated by all the previous points will be accumulated. After reaching the end point (o, n), this cumulative distance is the total distance, which is the similarity between the sequences m and z [19].

$$\alpha(u,l) = w(m_u, z_l) + \max\{\alpha(u-1,l-1), \alpha(u-1,l), \alpha(u,l-1)\}. \quad (5)$$

It is also critical to determine the character of a football player. Suppose we have o samples $\vec{a}_1, \vec{a}_2, \vec{a}_3, \ldots \vec{a}_o$. Project these o samples to a 0-dimensional vector $\vec{a}_o$, that is, a point, so that the sum of squares of the distance from this point $\vec{a}_0$ to these o samples is the smallest, as in (6), where $f_0(\vec{a}_0)$ represents the sum of squares of the distance [20].

$$f_0(\vec{a}_0) = \sum_{u=1}^{o} \|\vec{a}_0 - \vec{a}_u\|^2. \quad (6)$$

And the sample mean $\vec{n}$ can be expressed as $\vec{n} = 1/o \sum_{u=1}^{o} \vec{a}_u$; then for $f_0(\vec{a}_0)$, it can be expressed as follows:

$$f_0(\vec{a}_0) = \sum_{u=1}^{o} \|(\vec{a}_0 - \vec{n}) - (\vec{a}_u - \vec{n})\|^2. \quad (7)$$

Then, $f_0(\vec{a}_0)$ can be expressed as follows:

$$\vec{f}_0(\vec{a}_0) = \sum_{u=1}^{o} \|\vec{a}_0 - \vec{n}\|^2 + \sum_{u=1}^{o} \|\vec{a}_u - \vec{n}\|^2. \quad (8)$$

It can be seen from (8) that $f_0(\vec{a}_0)$ takes the minimum value at $\vec{a}_0 = \vec{n}$. In the case of 0 dimensions, the best projection of the sample in the sense of the smallest mean square error is the mean of the sample points [21].

Let $\vec{f}$ denote the unit direction vector passing through the sample mean line $\vec{n}$, then the line $\vec{a}$ can be expressed by $\vec{f}$ and $\vec{n}$ as follows:

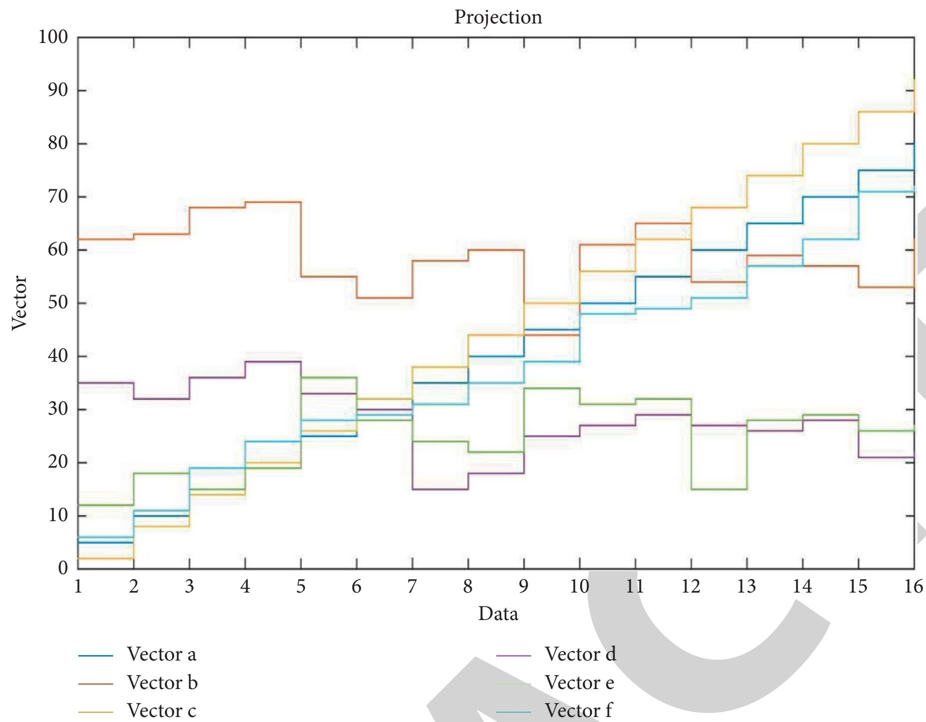

Figure 3: Schematic diagram of sample data mapping to one-dimensional.

$$\vec{a} = \vec{n} + x\vec{f} * \sum_{\exp}^{u=1}(u_a, u_b), \quad (9)$$

where x is a real number. The projection of the sample $\vec{a}_u$ in the $\vec{f}$ direction is shown in Figure 3.

As shown in Figure 3, $\vec{X}_u = |\vec{a}_u - \vec{n}| z\,pt(\varpi_u)$ can be obtained from the vertical relationship, where ϖ_u is the angle between the vector $\vec{f}$ and the vector $\vec{a}_u - \vec{n}$. Since $\vec{f}$ is a unit vector, the mean square error $f_1(\vec{f})$ can be expressed as [22]

$$f_1(\vec{f}) = \sum_{u=1}^{o} \left\| \left(\vec{n} + x_u \vec{f}\right) - \vec{a}_u \right\|^2. \quad (10)$$

Data acquisition is an application system that uses a wireless module and sensor to collect data from outside the system and input it into the system for data statistics. The nonelectricity or electric quantity signal is automatically collected from the digital unit under test and sent to the computer system for analysis. Combined with the expression of x_u, it can be derived that the mean square error $f_1(\vec{f})$ can be expressed as [23]

$$f_1(\vec{f}) = -\vec{f}^{s}\left(\sum_{u=1}^{o} \vec{a}_u - \vec{n}\right)\left(\vec{a}_u - \vec{n}^{s}\right)\vec{f} + \sum_{u=1}^{o}\left\|\vec{a}_u - \vec{n}\right\|^2. \quad (11)$$

Multiply both sides of the formula by $\vec{f}^{s}$ at the same time to get formula

$$\vec{f}^{s} t \vec{f} = \beta \vec{f}^{s} \vec{f} = \beta. \quad (12)$$

According to formula (12), when the sample data are projected to the direction of the eigenvector corresponding to the largest eigenvalue of the scatter matrix (defined as the β direction), $\vec{f}^{s} t \vec{f}$ takes the maximum value [24].

When the sample data are projected to the g dimension, the conclusion of 12 shows that the projection to the g dimension space can be expressed as $\vec{a} = \vec{n} + \sum_{j=1}^{g} x_j \vec{f}$, and the minimum mean square error is shown in the following formula:

$$f_g\left(\vec{f}_1, \vec{f}_2, \ldots\ldots \vec{f}_g\right) = \sum_{u=1}^{o}\left\|\left(\vec{n} + \sum_{j=1}^{g} x_{uj}\vec{f}_u\right)\right\|^2. \quad (13)$$

It can be proved that $f_g(\vec{f}_1, \vec{f}_2, \ldots\ldots \vec{f}_g)$ obtains the minimum value when the vector $\vec{f}_1, \vec{f}_2, \ldots\ldots \vec{f}_g$ is the eigenvector corresponding to the first g eigenvalues of the scatter matrix t [25]. All the quantities belonging to this g-dimensional space can be represented by $\vec{f}_1, \vec{f}_2, \ldots\ldots \vec{f}_g$, as shown in

$$\vec{a}'_u = \vec{n} + \sum_{u=1}^{g} x_{uj}\vec{f}_j. \quad (14)$$

Among them,

$$x_{uj} = \vec{f}_j \bullet \left(\vec{a}_u - \vec{n}\right) = \vec{f}_j^{s} \bullet \left(\vec{a}_u - \vec{n}\right). \quad (15)$$

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Table 1: Distribution of male football training years in school.

Group	1–3 years	4–5 years	6–7 years	7 years or more	Total
Number of people	22	49	59	31	161
Proportion (%)	14.9	34.1	39.2	11.8	100.0
Eccentricity (100%)	96.6	94.8	95.8	96.3	100.0

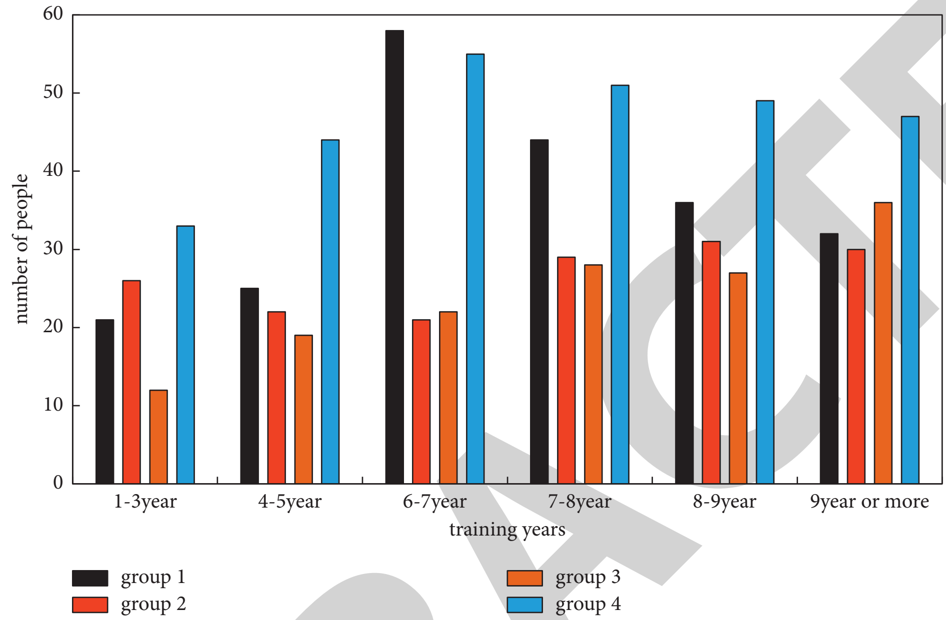

Figure 4: Distribution of male football training years in school.

$x_{u1}, x_{u2}, \ldots\ldots x_{ug}$ is the main component, and a lower dimension is used to represent the original sample data [26].

3. Experiments and Conclusions of the Design and Implementation Method of Moving Data Analysis in Football Training Based on Embedded Action Recognition

3.1. Subjects. The subjects of this study are 322 school boys in a certain city. We investigated 29 youth teams in a certain school with football training experience, 52 people from 14- to 15-year-old city clubs, 32 youth football teams in a certain school, 22 people in a middle school, and 26 people in a county second middle school football team, totaling 161 people in the city's 5th middle school without football training experience.

In order to study the influence of different football training years on the analysis of the city's school boy's position data, this study divided the school boys with football training experience according to different training years, which can be divided into 1–3 years, 4–5 years, four groups: 6–7 years, 7 years, or more. The distribution statistics of personnel in each group are shown in Table 1 and Figure 4.

It can be seen from Figure 4 that most of the school boys in the survey have more than 6 years of football training experience. This is because the city has a strong football culture atmosphere. With the encouragement of the school or the support of parents, many boys have been in elementary school, began to participate in football, and developed a strong interest in football, which prompted school boys to often participate in football. As the receiver of knowledge, athletes have great subjective initiative. A football team consists of more than 20 players. Sometimes, the number of training camps reaches more than 30 people. Each player has different growth and life experiences, and the characteristics of competitive ability are quite different. A comprehensive and accurate understanding of the players' competitive ability is characterized by the main basis for coaches to choose technical and tactical play for the team.

3.2. Design of Action Information Collection System. Inertial sensors are used as acceleration sensors and rotators, and the corresponding inertial values are speed increase and edge velocity; electromagnet is a resistive sensor, and the output value is magnetic field strength; the image sensor is a K sensor, and the output value is color image, depth image, and bone information [27–29]. The inertial sensors and magnetic sensors at the data collection end are collected by wearing on human limbs. For example, the sensor segment points can be fixed on the thigh, calf, and ankle in the gait motion collection experiment; the segment points can be fixed on the waist during the fall experiment, the head, etc.; segment points can be fixed on multiple parts of the human body in the human body's daily behavior and action experiment.

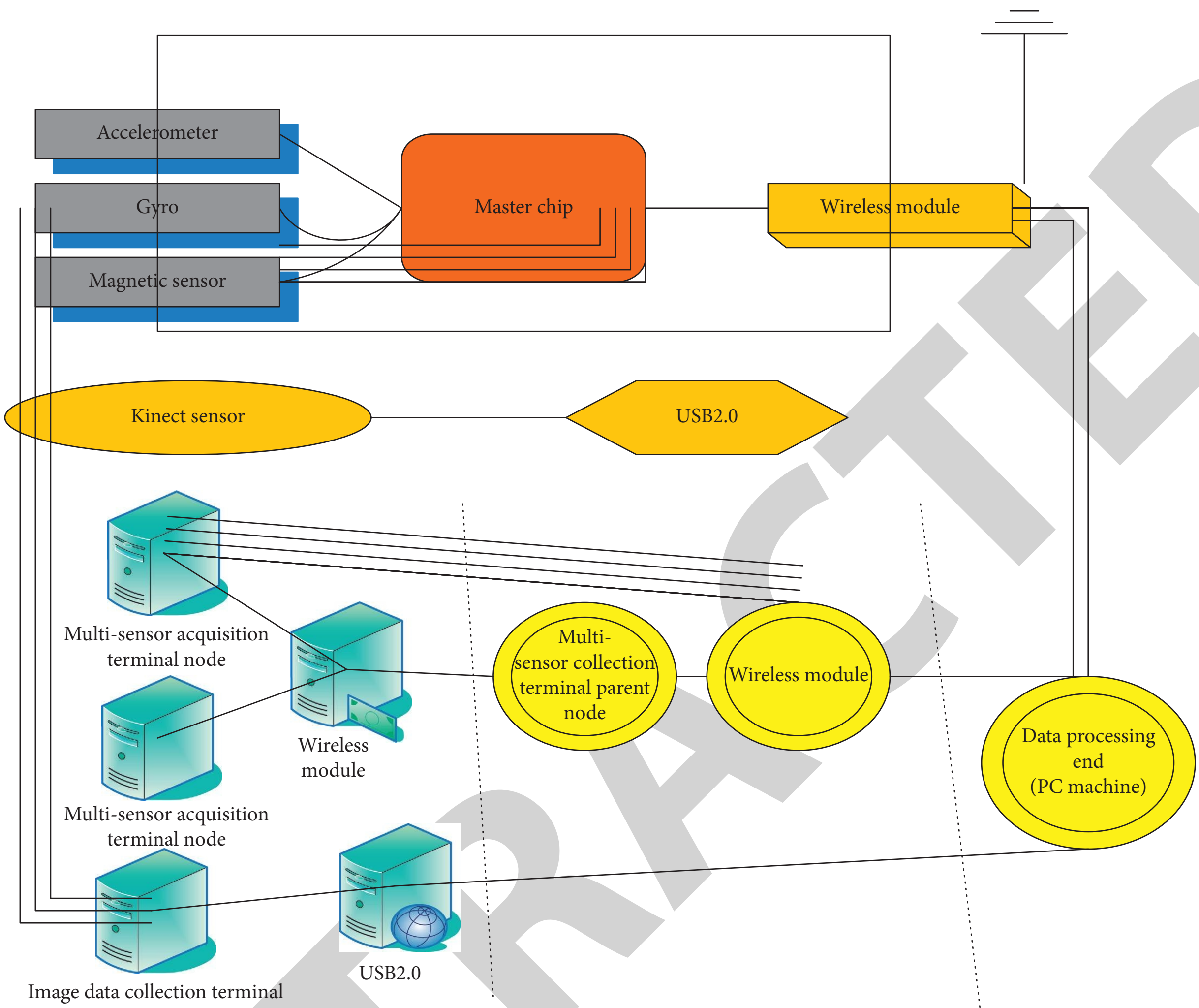

Figure 5: Block diagram of body movement data acquisition system.

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The main functional requirements of the data collection terminal are as follows:

(1) Collecting segment points can accurately collect three-axis acceleration, three-axis angular velocity, and three-axis magnetic field data.

(2) Collecting segment points can perform simple processing on nine-axis data, such as setting thresholds and filtering.

(3) The number of acquisition segment points and the output rate are configurable.

(4) The collection point requires small equipment size and weight, low power consumption, status display, and easy control.

(5) Data transmission methods include wireless and wired.

According to the above-mentioned demand analysis, a data acquisition terminal based on inertial sensors, magnetic sensors, and image sensors is designed, and its structure diagram is shown in Figure 5.

As shown in Figure 5, the multi-sensor collection terminal can be used as a child segment point or as a parent segment point. When used as a parent segment point, the sensor collection function is turned off, and the polling method is used to collect the data of each sub-segment point; when a set of data is collected, it is uploaded to the data processing terminal through the wireless module.

3.3. Sensor Configuration. The important registers of MPU6112 are shown in Table 2.

The important registers of HMC5698 are shown in Table 3.

The initial configuration of HMC5698 is sampling rate configuration, 8 sampling data for one measurement data output, output rate configuration 28 Hz, measurement mode configuration, and range selection.

3.4. Human Model Establishment. To use a computer to collect movement information and recognize body movements, it is first necessary to establish a reasonable human body model based on the human body structure and kinematics theory. The human body is a very complex structural complex, including its own sensing system,

Table 2: Register configuration of MPU6112.

Register name	Register address	Description
SLA	$0.1 \times d1$	Register operation address
SMP	0.1×20	Sampling rate divider
PWR	$0.1 \times 5B$	Power management and clock configuration
CON	$0.1 \times 2a$	Low-pass filter configuration
CYR	$0.1 \times 2b$	Gyro self-test and range selection
ACC	$0.1 \times 2c$	Accelerometer self-test and range selection
INT	0.1×40	Interrupt configuration
GYO	$0.1 \times 42 \sim 0.1 \times 47$	Angular velocity data register group
ACO	$0.1 \times 2b \sim 0.1 \times 37$	Acceleration data register group

Table 3: Register configuration of HMC5698.

Register name	Register address	Description
SLA	$0.1 \times 2c$	Register operation address
CON	0.1×0.01	Selection of sampling times and output rate
CON	0.1×02	Range selection
MO	0.1×03	Measurement mode selection
DX	$0.1 \times 04 \sim 0.1 \times 05$	X-axis magnetic field data ($0 \times f800 \sim 0 \times 7ff$)
DY	$0.1 \times 08 \sim 0.1 \times 09$	Y-axis magnetic field data
DZ	$0.1 \times 06 \sim 0.1 \times 07$	Z-axis magnetic field data
STA	0.1×10	Data register status monitoring

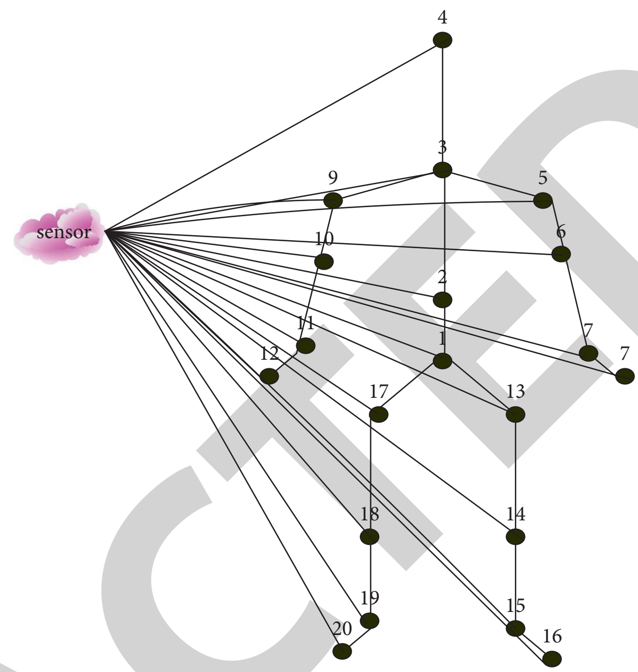

Figure 6: Human body joint map.

Table 4: Mean available start frame.

Number of acquisition frames	25	55	75	95	105	205
No delay	22	18	18	21	18	19
Delay 2 s	3	2	5	4	6	1
Delay 5 s	1	2	1	2	1	2

processing system, and control execution system. Skeletonization and segmentation of the human body based on the bones of the human body can effectively reflect the state of the human body. From a spatial perspective, the recognition of two-dimensional models is relatively simple. The traditional skeleton extraction scheme is based on two-dimensional images. The algorithm is effective in processing the background environment, high contrast, and high camera accuracy. The three-dimensional human body model is compared with the two-dimensional, and the model has more depth data dimensions, contains the main information of the human body in space, and can accurately estimate the human body's spatial movement.

As shown in Figure 6, it is a diagram of the main segments of the human body. It can be seen from the figure that the segments of the human body are connected to the trunk, limbs, head, etc., including the finger, wrist, elbow, knee, and chest lock-off paragraph. The determination of these points also establishes the model foundation of the human body. The information of the three-dimensional human body model mainly includes the spatial positioning, connection relationship, and distance of the various points. The three-dimensional model used in this article is a 3D skeleton model of 20 main points. The 20 points are 1. hip center; 2. spine; 3. shoulder center; 4. head; 5. left shoulder; 6. left elbow; 7. left wrist; 8. left hand; 9 right shoulder; 10. right elbow; 11. right wrist; 12. right hand; 13. left hip; 14. left knee; 15. left ankle; 16. left foot; 17. right hip; 18. right knee; 19 right ankle; and 20 right foot. And each is connected to the sensor.

3.5. Survey Samples and Analysis. Use MATLAB to extract the K bone information, the human body is facing the K device when collecting, the number of acquisition frames is, respectively, selected as 25, 55, 75, 95, 105, and 205, and each frame number is collected 10 times and averaged. When the image and depth sensors are turned on and the data are collected immediately, the bones cannot be tracked in the first 20 frames of the image; while the data are collected after a few seconds of delay in turning on the sensor, there is basically no loss of bone frames, as shown in Table 4. The subsequent experiments are based on the acquisition after the startup delay, the delay time is 4s, and it can provide preparation time for the action at the same time.

Since the 20 key bone point outputs by K come from the RGB camera and infrared camera on the same side, the human skeleton is subject to color images and depth images in most cases, and is still affected by the environment, especially environmental occlusion and limbs. Severe distortion may occur in situations such as overlap.

In the experiment, the occlusion situation is the body's own occlusion and the partial occlusion of the environment.

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Table 5: Tracking status and node status of different postures.

Action posture	Tracking status					Node status
	1	2	3	4	5	
Upright	1	1	1	1	1	Good
Oblique	1	1	1	1	1	Good
Side stand	0	0	0	0	0	No
Right arm pointing to the device	0	1	1	1	0	Poor
Behind the right arm	1	1	1	1	1	Bad
Right arm bent upward	1	1	1	1	1	Poor
Right leg environmental occlusion	1	1	0	1	1	Bad

Seven different static action poses are selected, and data are collected for each group of poses 5 times. The number of frames for each collection is 110 frames, and the bone state is obtained as shown in Table 5. 1 indicates tracking success, and 0 means tracking failure.

Except for standing upright and obliquely standing, good bone information can be obtained, and other occluded action postures have more or less bad and unrecognizable bone segment point information. Among them, the tracking state is all invalid in the side standing motion, and due to the lack of body and right body information, the bone information cannot be recognized; when the right arm is pointing to the device, there is 1 tracking failure, and when the right arm is pointing to the sensor, the image and depth sensor only recognizes the right-hand information. The obtained right wrist and right elbow information may be wrong; the partial occlusion of the right leg has 2 tracking failures; the middle axis segment point (head-shoulder center-spine-hip center) in the segment point information is good and poor The point state mainly appears on the segment points of the limbs. For example, the point information of the occlusion behind the arm and the partial occlusion of the body is severely shifted. It can be seen that when the main body of the torso is occluded or affected by environmental background factors, the bone information is prone to be unrecognizable; at the same time, the bone segment points under the occlusion of the right arm and right leg show that the data output by the device is largely dependent on image sensor.

3.6. Test Results after Compensation. Wear sensors are on the thigh and the middle of the calf, the measured value of the thigh length $L1$ is 0.6 m, and the value of the calf length $L2$ is 0.4 m. The right knee compensation data are based on the right hip data, and the right ankle is based on the compensated right knee data. A and b are the points of the skeleton before and after compensation. Relatively, there is a right-hand occlusion posture. This time the right ankle point is at coordinate compensation is performed on the basis of the right knee. When the environment is occluded, the right leg does a leg-raising exercise, first raising the leg and then lowering the leg to get the coordinates of the right knee and right ankle as shown in Figure 7.

It can be seen from Figure 7 that the motion basically keeps moving in the bc plane, the a-axis coordinate should be changed less, and the bc-axis data should be changed more. Take the right knee as an example. When the leg is raised, the b-axis coordinate increases, and the c-axis coordinate decreases. When the leg is dropped, the opposite is true. It can be seen that the compensated coordinates are consistent with the action.

4. Discussion

4.1. Article Context Analysis. First introduce the deep learning tool Caffe, and then introduce the principle and implementation of each layer of the deep convolutional neural network. Finally, an 11-layer convolutional neural network was designed for the embedded platform, and the network was implemented using Caffe. The training model and network are deployed on the embedded platform and tested on different action data sets, and analyzed the reasons that affect the recognition accuracy. In view of the fact that the embedded platform has limited computing power compared with the advanced graphics cards and server clusters on the PC side, and the data set is noisier, the test results basically met the initial requirements.

4.2. Summary Analysis. To sum up, although the concept of sensors has been proposed for ten years, as a data integration technology with considerable benefits and performance, whether from books or engineering research levels, it still requires a lot of development by scholars and workers to truly mature. In terms of book copying, however there are many attractive features when it is proposed, such as the high efficiency of the network and strong research. However, there are still big deficiencies in the research of contracts, such as how to make reasonable plans for the modules of each segment in an extremely complex network structure, and try to increase the duration of the entire network. Also in terms of research engineering, there are now many universities and research institutes doing experiments in this area, and many companies have already produced some powerful transmission components and methods, but in general, wireless sensors. The network has not yet fully entered the large-scale practical development process. However, it can be expected that in the next few years, with the innovation and development of theories and the endless supply of new methods, those related network projects that are still in fading will leave the laboratory and enter every aspect of our lives again and again.

4.3. Model Analysis. So far, the design of the sports data acquisition system suitable for football stadiums has been completed. Although this system is still in the experimental debugging stage, it can be seen that the basic functions of the system have been realized. This system is mainly based on the theory of wireless sensor network, the single-chip microcomputer plus wireless transmission module is the hardware, and the interface program and protocol are the software. In this article, from the initial selection of this application, to the design of two hardware solutions, to the design of the final graphical interface, a more detailed

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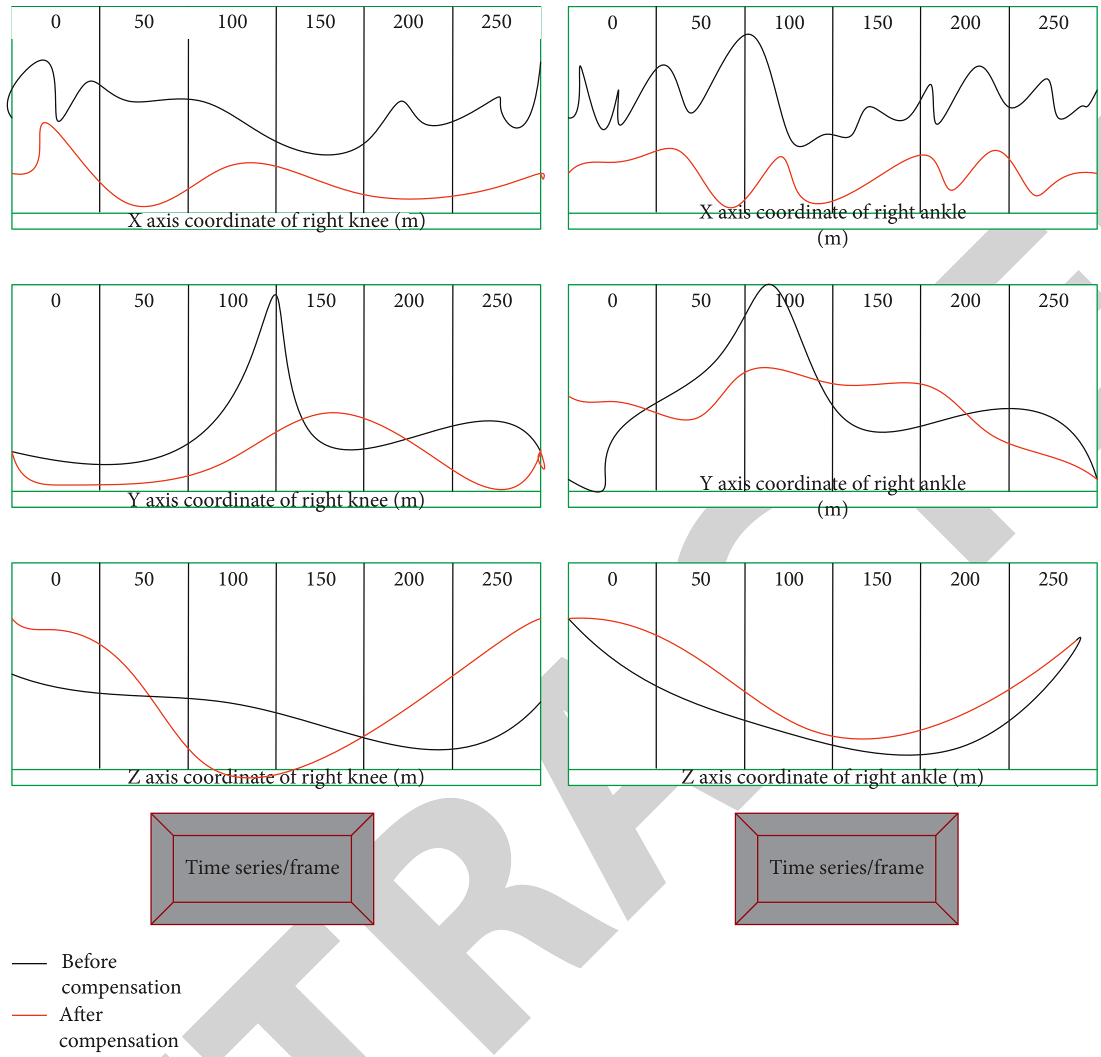

Figure 7: Right knee and right ankle space coordinate.

description is carried out. In the next step, I will test and evaluate this system to determine the final realization scheme.

5. Conclusions

The corresponding process of hand and foot movement is one of the advanced methods in the field of humans and machines. This technology can be developed in the fields of medicine, development process, surveillance, sports, and football recognition. In order to deeply study the relevance of the embedded action recognition system in collecting football training positioning data, this paper uses simulation model establishment method, data collection method, and theory and practice combination method to collect samples, analyzes the embedded action recognition system, and streamlines the algorithm. The initial configuration of HMC5698 is sampling rate configuration, 8 sampling data for one measurement data output, output rate configuration 28 Hz, measurement mode configuration, and range selection and creates an action recognition system that can record the position data in football training. After establishing the human body simulation recognition model, use MATLAB to extract the K bone information. When collecting, the human body is facing the K device, and the number of acquisition frames is 25, 55, 75, 95, 105, and 205, and each frame number is collected 10 times. Take the average. The delay time is 4s. The result shows that the 20 key bone point outputs by K come from the RGB camera on the same side. Further study the actual utility of the compensated model in the presence of occlusion. They are worn on the middle of the thigh and calf, respectively. In a sensor, the measured value of thigh length L1 is 0.6 m, and the value of calf length L2 is 0.4 m. Take the right knee as an example. When the leg is raised, the b-axis coordinate increases by 2%, and the c-axis coordinate decreases by 1.8%. When the leg is lowered, the opposite is true. It can be seen that the compensated coordinate is consistent with the action. The shortcomings of this paper are as follows: first of all, large-scale wireless sensor networks need to be researched and tested, because when the number of network segments increases, the network communication performance will drop sharply. This point has been fully

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demonstrated in the 5 g network; secondly, the segment energy design of the segment point needs further research; after all, it seems that its energy consumption is still too large. Therefore, in further research, the network performance should also be targeted to improve, and lithium battery supply should be selected in terms of power consumption to reduce energy consumption, so that more football fields can be applied to this action recognition system.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Disclosure

The author received no financial support for the research, authorship, and/or publication of this article.

Conflicts of Interest

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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