



## SVM-BASED SUPPORT VECTOR TYPE RECOGNITION MACHINE FOR SMART THINGS IN SOCCER TRAINING MOTION RECOGNITION

SHOUWEI WANG\*

**Abstract.** With the development of IoT technology, machine learning, and other artificial intelligence technologies, there have been many related technologies applied to the sports industry. Soccer, as the world's number one sport, has a wide range of popularity, a high degree of attention, and a high degree of commercialization. In the traditional soccer training action recognition methods, there is insufficient collection and in-depth profiling of real data, and what is not available is soccer movement action capture and recognition based on kinematic knowledge. To address the above shortcomings, this study designs a Support Vector Machine SVM-based intelligent IoT-type soccer training movement recognition and evaluation framework, and constructs a machine learning algorithmic model to recognize, evaluate and analyze soccer training movements. Common feature extraction methods are suitable for recognizing most monotonous movements, but soccer movements are highly variable and athletes' ankle movements are flexible and changeable. The actual acquired soccer data streams are noisy and the data patterns are not obvious, and the performance of the model to recognize the data will be degraded. To extract the effective feature values in the complex data stream and improve the correct degree of pattern recognition, the classification pattern of attitude angle type solving + SVM classification algorithm is constructed. The experimental results show that the designed algorithmic pattern based on the posture angular pattern solving + SVM classification algorithm pattern for soccer training movement recognition can reach 90% accuracy in recognizing different movements, which is extremely suitable for the recognition of soccer training movements.

**Key words:** smart internet of things; soccer ball movement recognition; stance angular pattern; SVM

**1. Introduction.** The new era of communication and information technology is becoming more and more developed, and the application of intelligent Internet of Things-type technology is becoming more and more widespread [1]. Its application field involves industry, agriculture, transportation, and other infrastructure fields, effectively promoting the intelligent development of various industries [2]. In contrast, the application of IOT technology in sports is still in the primary exploration stage. Combining intelligent IOT technology and machine learning algorithms to realize human-machine and human-network system-human interaction using inertial sensor-based motion capture has become an international cutting-edge research hotspot involving a high degree of multidisciplinary crossover and knowledge integration [3, 4]. The researchers have been working hard to realize the human-machine interaction using inertial sensor-based motion capture.

As the No. 1 sport in the world, soccer is widely popular, highly regarded, and commercialized. With the acceleration of urbanization in China, people's living standards and quality are improving, and the number of people who participate in soccer in their daily lives is also increasing [2]. In this context, there exists a great application demand and development potential for combining intelligent IoT-type technology and machine learning algorithms to be applied to the teaching, training, and even competition of soccer. Soccer training movement recognition and analysis mainly focuses on motion capture and evaluation of the athlete's lower legs and ankles, etc., and utilizes machine learning algorithms to recognize the movement movements and estimate the intensity of the movement. Overall, soccer players have very low sensitivity to motion recognition, and soccer players' footwork is difficult to recognize, there are very large differences in soccer players' behavioral logic, which are used by current soccer action methods for motion recognition. There is insufficient collection and in-depth profiling of real data, and what is not available is soccer movement action capture and recognition based on kinematic knowledge. The current model does not analyze the complex and high-noise action data stream deeply enough [1, 5].

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\*School of Public Foundation, Henan Vocational College of Information and Statistics, Zhengzhou 450000, China ([wangshouwei123@yeah.net](mailto:wangshouwei123@yeah.net))

The automation of flight training quality assessment using soccer training movement data must do the following two things:

- ? the data source is sufficient and accurate, which can correctly reflect all kinds of movements in soccer training;
- ? automatically recognize the movements made by the players.

With the development of hardware conditions, the first requirement has been able to satisfy relatively well, while the second condition, i.e., the research in the field of deep analysis of players' movement parameters, has been a blank so far. Soccer training action recognition can be reduced to a pattern recognition problem, however, traditional statistical pattern recognition methods such as linear classifiers (Fisher discriminant, MSE algorithm) are too simple, the Bayes method is difficult to implement, and the generalization of artificial neural networks is weak, etc. have one or another problem. The traditional extraction method for soccer action recognition is to decompose the action-based footwork into features. However, this kind of behavior suffers from problems such as a low degree of correct extraction in high-level soccer sports competitions [6, 7].

Common machine learning methods are suitable for recognizing most monotonous movements, but soccer movements are highly variable and players' ankle movements are flexible. The actual acquired soccer data streams are noisy and the data patterns are not obvious, and the performance of pattern recognition on the data will be degraded. To extract the effective feature values in the complex data stream and improve the correct degree of pattern recognition, we construct a classification pattern of attitude angle solving + Support Vector Machine (SVM) classification algorithm for small-sample data with less influence of noise and adapted to the recognition of soccer movements in this study.[8] The SVM algorithm model is suitable for small-sample data with less influence of noise and suitable for recognizing soccer moves in this study.

Based on the above research background and significance, this paper researches the method of soccer training action data analysis based on intelligent IOT type, according to the shortcomings of the existing related research and the needs of the practical application scenarios, it designs the framework of soccer movement recognition and evaluation, collects the soccer movement data, and constructs the algorithmic mode of machine learning to recognize, evaluate and analyze the soccer movement, and it becomes possible to apply intelligent IOT type technology and SVM algorithm applied to the recognition and analysis of soccer training movements becomes possible, providing a new way to add the efficiency of training. And Ethical considerations should be emphasized when applying IoT and machine learning in sports training. Protect the privacy of athletes to ensure legal and compliant use of data; respect the right to informed consent by clearly communicating the use of data and obtaining consent; reduce data bias and improve model accuracy; avoid over-reliance on technology and respect the rights and interests of athletes. Follow ethical principles to ensure reasonable and compliant use of technology.

**2. SVM Model and Algorithm.** Support Vector Type Recognition Machine [9, 10] One of the most influential results in the last few years, This algorithm is a solution for re-identifying the type of analysis in a layer type of data related to the volume of the data., and the more solid theoretical foundation makes it well generalizable. With other tried-and-true amplifications such as LR-type methods, SVMs are often used for higher-order types or linearly inseparable solution answers, which are free to choose the parameter model and use the set of supported type vectors as the basis for the classification of the hyperplane, the problem in this study belongs to a small-sample linearly indivisible problem, and therefore the SVM algorithm pattern is chosen to solve it [11].

### 1. Support vector type recognizer

The mathematical description of the two types of support vector type discriminators is as follows [12, 13]: Given the training sample data can be separated by the hyperplane. A hyperplane is an optimal hyperplane if the data type between the closest sample to the hyperplane and the hyperplane is maximal. The optimal hyperplane possesses the type that is the best solution to get the minimization  $\|w\|/2$  with the constraint  $y_i (w^T \cdot x) + b \geq 1$ . Using the pairwise rule, the linearly divisible optimization problem can be simplified to maximize

$$\left. \begin{aligned} \text{Max } W(\alpha) &= \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i y_i \alpha_j y_j (x_i \cdot x_j) \\ \text{restrict } \sum_{i=1}^n \alpha_i y_i &= 0, \quad \alpha_i \geq 0, \quad i = 1, \dots, n \end{aligned} \right\} \quad (2.1)$$

where  $a = 0 (a_1, \dots, a_n)$  is the Lagrange multiplier, and the samples corresponding to  $a_i \neq 0$  become support vectors;  $a''$  denotes the Lagrange multiplier corresponding to the support vector; and  $W(a)$  is a function of the Lagrange multiplier  $a$ . The value of  $b$  can be obtained from the KKT condition, the linear case

$$b = \frac{1}{2} \sum_{k=1}^n y_k \alpha_k^* (x_1 \cdot x_k + x_2 \cdot x_k) \quad (2.2)$$

where  $x_1$  and  $x_2$  are the support vectors for either of the two types of samples, respectively. Decision functions for support vector type recognizers, linear case

$$D(x) = \sum_{i=1}^n \alpha_i^* y_i (x_i \cdot x) + b \quad (2.3)$$

Sample  $x$  belongs to the following category

$$x \in \left\{ \begin{array}{l} \text{type 1} D(x) > 0 \\ \text{type 2} \text{else} \end{array} \right\} \quad (2.4)$$

If you apply a kernel function that satisfies the Mercer condition

$$kx, y == \Phi(x) \cdot \Phi(y) \quad (2.5)$$

Then there is no need to obtain the type form of the solution, which is a distinctive feature of support vector-type discriminators [4], and the kernel-type solution function implements the nonlinearization of the algorithm. The kernel-type solution function is

$$kx, y = xTy \quad \text{dot product kernel} \quad (2.6)$$

$$k(x, y) = (xTy + c)d \quad \text{polynomial kernel} \quad (2.7)$$

$$k(x, y) = ex - 12 \quad \text{radial nucleus} \quad (2.8)$$

where  $d$  is the number of polynomial kernel functions. With the kernel function, the nonlinear form of Eqs. (2.1), (2.2) and (2.3) can be expressed as

$$\left. \begin{array}{l} \max W(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j (x_i \cdot x_j) \\ \sum_{i=1}^n \alpha_i = 0, \quad 0 \leq \alpha_i \leq C, \quad i = 1, \dots, n \end{array} \right\} \quad (2.9)$$

$$b = -\frac{1}{2} \sum_{k=1}^n y_k \alpha_k^* [K(x_1 \cdot x_k) + K(x_2 \cdot x_k)] \quad (2.10)$$

where  $x, x_1,$  and  $x_2$  are the support vectors of either of the two sample classes, respectively. Sample  $x$  belongs to the following category

$$x \in \left\{ \begin{array}{l} \text{type 1} D(x) = 1 \\ \text{type 2} D(x) = -1 \end{array} \right\} \quad (2.11)$$

## 2. Multi-class support vector type recognizer

Traditional N-class support vector type discriminators solving multi-class classification are usually transformed into N two-class problems, i.e., one-to-many classifiers[14, 15]. N two-bounded classifiers are constructed for the N-level problem, and the  $i$ th SVMs use the data in the  $i$ th level as positive

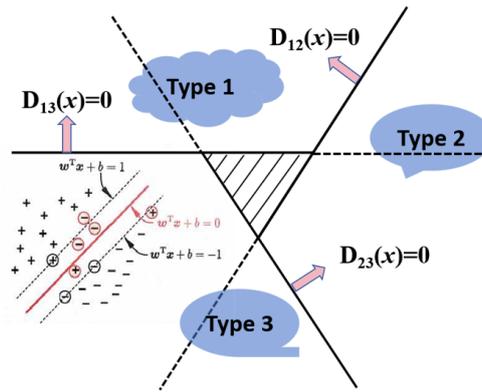


Fig. 2.1: Unclassifiable regions for one-to-one classification

training samples and the others as incorrect hypothesis samples [16]. This algorithm is called 1-a-r (1-against-rest). Let the *i*th decision function in level *i* be

$$D_i(x) = wx + b \tag{2.12}$$

level when  $D_i(x)=0$  is the optimal type solution;  $D_i(x)=1$  is a low-level SVM, and the others satisfy  $D_i(x)=-1$ . For traditional SVMs to recognize type-level machines, if the collected type data  $x$  is satisfied only for an  $I$ , i.e.

$$D_i(x) > 0 \tag{2.13}$$

then  $x$  belongs to class  $i$ .

If Eq. (2.13) is right for more than one  $i$  or not at all; Eq. (2.13) is satisfied so that an indivisible region is produced. To solve this problem, dual classifiers are proposed[14], which constructs all possible two-class classifiers in  $N$  classes of training samples, and each class is trained on just 2 of the  $N$  classes of training samples, resulting in the construction of a total of  $N(N-1)/2$  classifiers, and the algorithm is called 1-a-1(1-against-1)[17]. Let the decision function between class  $I$  and Class  $j$  be

$$D_{ij}(x) = w_{ij}^T x + b_{ij} \tag{2.14}$$

where  $D_i(x) = -D_j(x)$ . For the vector  $x$ , we have

$$D_i(x) = \sum_{j=1, j \neq i}^n \text{sign}(D_{ij}(x)) \tag{2.15}$$

and  $x$  is solved at type level  $\arg \max D_i(x)$ .

To test the effectiveness of the algorithm, a fuzzy support vector type recognizer is applied to the recognition of flight patterns [18].

### 3. Methods of recognizing soccer training movements.

**3.1. Acquisition of soccer training movement data.** This study was conducted in a standard soccer field for data collection experiments. A total of 30 soccer players were recruited, including 5 female and 25 male soccer players. They were asked to perform passing and shooting using various positions on a turf-type soccer field.

Figure 3.1 shows the soccer players when they performed passing and goal shooting. Acquiring soccer player action images is a prerequisite for extracting training action features. Since the action images acquired

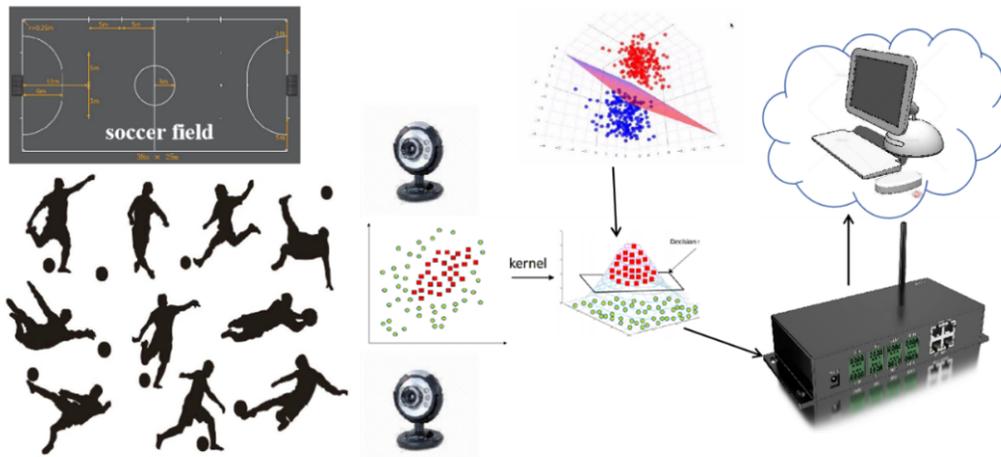


Fig. 3.1: Experimental setup for action data acquisition in a smart IoT-type system

Table 3.1: Number of pixel elements per segment in signal columns and signal rows of motion images

| HSYNC Signal Column | Number of elements | VSYNC Signal Column | Number of elements |
|---------------------|--------------------|---------------------|--------------------|
| Paragraph (a)       | 256                | Paragraph (o)       | 5                  |
| Paragraph (b)       | 347                | Paragraph (p)       | 49                 |
| Paragraph (c)       | 1589               | Paragraph (q)       | 1568               |
| Paragraph (d)       | 32                 | Paragraph (r)       | 2                  |
| Paragraph (e)       | 1786               | Paragraph (s)       | 1422               |

by traditional methods have large visual errors, which directly affect the degree of correct extraction of foul action features, for this reason, this paper utilizes an intelligent IoT-type system to acquire soccer player action images.

In the smart IoT-type system, the use of cameras to obtain images of soccer players in action can be achieved by selecting the OV7670 model camera. The OV7670 model camera is a CMOS camera element, with the ability to obtain color images, and the sensitivity array can reach up to  $640 * 680$ , the transmission rate of up to 30 frames / s. The OV7670 model camera is a CMOS camera element, with the ability to obtain color images, a sensitivity array up to  $640 * 680$ , and a transmission rate of up to 30 frames / s.

The camera has only one set of parallel data ports, noted as Y [7], through the data port to read the pixel value of the action image to obtain the soccer player training action in parallel. The OV7670 camera to obtain images of the components of the PL and PS, based on the line interrupt and field interrupt to determine the completeness of the data to use the VGA interface to display the soccer player training action images.[19] The VGA timing is shown in Figure 3.2. Wherein Data denotes a column of motion picture information; HSYNC and VSYNC denote a signal column and a signal row; (a), (b), (c), (d), and (e) denote the HSYNC signal column synchronization segment, the rear gallery segment, the activation segment, the front gallery segment, and the number of column elements, respectively; (o), (p), (q), (r), and (s) denote the VSYNC signal row synchronization segment, the rear gallery segment (o), (p), (q), (r) and (s) represent the number of VSYNC signal row synchronization segments, rear corridor segments, activation segments, front corridor segments and row elements, respectively.

The number of pixel elements per segment in the signal columns and signal rows of the motion picture is shown in Table 3.1.

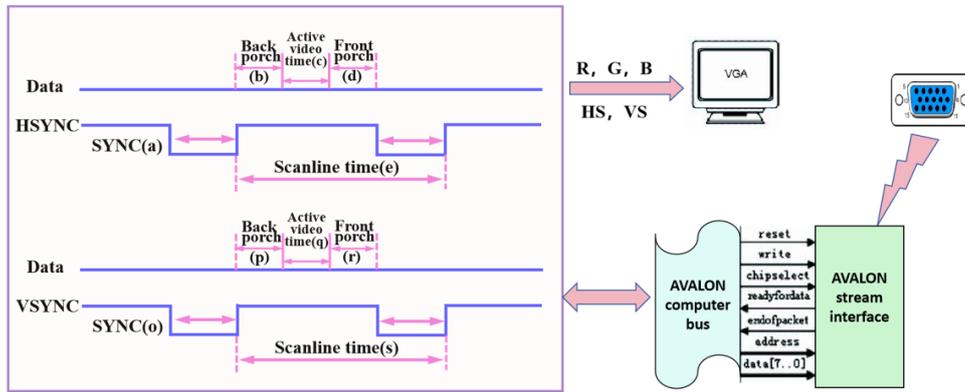


Fig. 3.2: VGA Timing Schematic

**3.2. Pre-processing of soccer training movement data.** Each frame of the experimenter’s action image extracted from the video is processed in grayscale to establish a grayscale image database and divide the training and test sets; each frame of the experimenter’s action image extracted from the video is processed using background subtraction and median filtering to generate a binary image library containing only the contours of the human body’s action[20].

The dimension of the action pictures is too large to cause the slow computing speed, to address this problem, PCA is used to downsize the training samples, extract the principal components, and downsize the feature vectors of each person’s action in the training set samples, so that the classification problem is simplified to the problem of dividing in the downsized space, to be the result of becoming for saving the time type and energy of arithmetic [21].

When an athlete is doing soccer training, the state of the action is continuously changing, however, due to the limitation of the sampling frequency of the parameters and the existence of random errors, the change of the parameters reflecting the state of the training action is not continuously and uniformly changing. To make the state changes of soccer training movements continuously and uniformly, it is necessary to take a period and average the parameters or the changes of parameters in this period [22, 23]. In the actual application of soccer training action data, it is necessary to expand the action data of 1 frame to 8 frames, and 3 frames will be expanded to 24 frames, so let  $p$  be the soccer training action data,  $m$  be the starting frame, and the converted soccer training action data  $p'$  is

$$p' = \frac{1}{24} \left( \sum_{i=0}^{23} p_{m+i} \right) \tag{3.1}$$

The extension of the data can be achieved by linear interpolation, where the values of the average distribution are then interpolated between the two neighboring parameters noted.

Because of the definition of the steering angle ( $0^\circ$  and  $360^\circ$  are in the same position), there may be an abrupt  $360^\circ$  change in the direction of the athlete’s rotation between two adjacent frames, e.g., the direction of motion is left from  $10^\circ$  to  $350^\circ$ . The athlete has turned only  $20^\circ$ , but when interpolating linearly, there will be some directional values between  $10^\circ$  and  $350^\circ$ , and the same for the roll angle.

For the direction angle  $360^\circ$  mutation, in the linear interpolation, set the change of heading angle as, if  $\Delta\phi > 180^\circ$ , then  $=\Delta\phi\Delta\phi - 360$ ; if  $\Delta\phi < -180^\circ$ , then  $=\Delta\phi\Delta\phi + 360$ ; the processing method of the roll angle is the same as that, and will not be described in detail here.

For an abrupt  $360^\circ$  change in heading angle, the following can be done in linear interpolation: let the change in heading angle be  $\Delta\phi$  :

If  $\Delta\phi > 180$  then  $=\Delta\phi\Delta\phi - 360$ ;

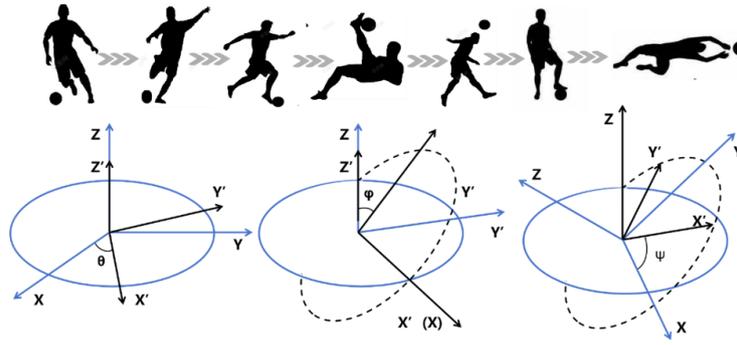


Fig. 3.3: Sectional of the attitude angular shape

If  $\Delta\phi < -180$  then  $=\Delta\phi\Delta\phi + 360$ ;

For an abrupt  $360^\circ$  change in roll angle, the following can be done in linear interpolation: let the change in roll angle be  $\Delta\Upsilon$  :

If  $\Delta\Upsilon > 180$  then  $\Delta\Upsilon = \Delta\Upsilon - 360$ ; if  $\Delta\Upsilon < -180$  then  $\Delta\Upsilon = \Delta\Upsilon + 360$ ;

**3.3. Soccer Motion Recognition and Assessment Models.** Soccer is more complex than other sports (e.g., badminton, tennis, and volleyball): the completion of the action mainly relies on the lower limbs the movement patterns are variable, and there are more ineffective lower limb actions and higher similarity between actions during the movement. Therefore, posture angular features based on the ankle area play a key role in improving the accuracy of movement classification, and more implicit movement feature information can be obtained through posture angular pattern solving to reflect the differences between movements, which helps pattern learning [24]. The model uses PCA to balance complexity and accuracy. The patterns are balanced in terms of complexity and accuracy using PCA; Then SVM-based classification algorithm is used to discriminate this type of soccer movement. Then the data are subjected to some advanced preparation type of operation, firstly the algorithm is to be used to smooth the type of drop of the collected data; then the peak of feature type is calculated by some small angle type of algorithm to automatically segment the data content of the sport recognition [25].

For the recognition of foot-based sports movements, in addition to the two important features of angular velocity and acceleration, the rotation of the ankle is also important in the recognition and evaluation of soccer movements, and mining the information of the stance angularity pattern can obtain the features containing more information in the movements. In this paper, we add a posture angularity pattern to extract more useful features [26]. The model is used in this paper to extract more useful features.

The attitude angular type consists of three types of variations of yaw angle, pitch angle, and roll angle of small angular types. Figure 3.3 demonstrates the angular type variation.

Typically, three-dimensional rotation problems are solved by rotation matrices [4, 27]. Quaternions are directional solution problems in the angle trace of the correct answer. The quaternion's representation model category is  $p\text{-pa} + p\text{ix} + p\text{y}\text{j} + p\text{z}\text{k}$  with one actual category  $p\text{e}$  and three imaginary category parameters  $p\text{x}$ ,  $p\text{y}$ , and  $p\text{z}$ . the attitude angular pattern is computed from equation (3.2):

$$\begin{cases} \theta = \arcsin(\alpha_{x0}) \\ \varphi = \arctan \frac{\text{mag}y_0}{\text{mag}x_0} \\ \psi = \arctan\left(-\frac{a_{y0}}{a_{z0}}\right) \end{cases} \quad (3.2)$$

where  $a_{y0}$  and  $a_{z0}$  represent the rate of increase,  $\theta$  and  $\psi$  represent the yaw, roll, and pitch of the initial category.

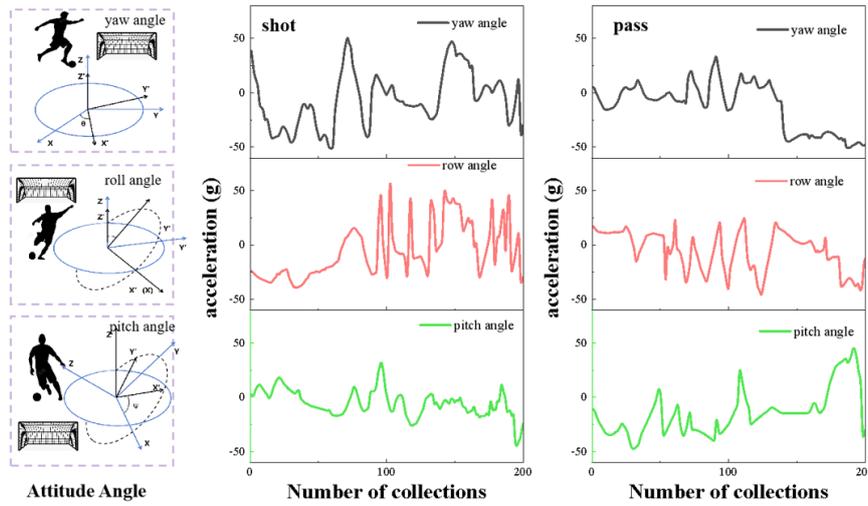


Fig. 3.4: Acceleration variation for different attitude angle patterns

The attitude angular pattern using quaternions is equation (3.3) [4, 28] :

$$\begin{cases} roll = \arctan \frac{2(p_0p_3+p_1p_2)}{1-2(p_0^2+p_1^2)} \\ pitch = \arctan \frac{2(p_1p_3-p_0p_2)}{4(p_0p_3+p_1p_2)^2+(1-2(p_0^2+p_1^2))^2} \\ yaw = \arctan \frac{2(p_0p_1+p_2p_3)}{1-2(p_2^2+p_3^2)} \end{cases} \quad (3.3)$$

The frequency was 100 Hz and then it was substituted to solve the stance angular pattern  $A_{n-i}$ . Figure 3.4 shows the comparison of the acceleration change for different stance angular patterns of shooting and passing in soccer training movements.

By dividing the  $A_{n-i}$  type and  $S_{n-i}$  type into one level of  $R_{n-i}$ , and then extracting the morphological type and level of the  $R_{n-i}$  segment, as shown in Table 2 [4, 29].

$F(n) = (f_i, f_{mn})$  is combined into a large 6xm matrix F. The procedure is shown in Fig. 3.5.

PCA is performed on the data that has been extracted to characterize the variables. Higher accuracy can be achieved by using the mode of PCA compared to other nonlinear dimensionality reduction methods. Suppose that the matrix type prime F has dimension type  $n \times m$ , i.e., there are a total of n data in dimension size of type m.

F is categorized into  $U\Sigma V^T$ , U with the same dimensions as F. The orthogonal type of matrix dimension V is  $m \times m$ , and  $\Sigma$  is a diagonal type of dimension matrix of the same type V. There is  $YU\Sigma^r = F(\Sigma V^T)$  (-1)  $\Sigma^r$ .

The extracted features from a vector feature of the summed type 42 dimensions, where  $F = [F1, F2, F34]$ . After going through the types of the process PCA, the new features obtained can be expressed as  $Y = [Yr1, Yr2, Yrm]$ , and m represents the computational dimension. There is equation (3.5):

$$Y_{rm} = F_1a_{ij} + F_2a_{ij} + \dots + F_ma_{ij} \quad (3.4)$$

$$Y_{rm} = F_1a_{ij} + F_2a_{ij} + \dots + F_ma_{ij} \quad (3.5)$$

where  $a_j$  is a special type of covariance type size. Equation (2.10) may be conveniently viewed as Eq. (3.6):

$$Y_{rm} = F_1a_1 + F_2a_2 + \dots + F_ma_m \quad (3.6)$$

Table 3.2: Feature selection

| eigenvalue (math.) | define  | eigenvalue (math.) | define   |
|--------------------|---|--------------------|--|
| Ray.               | incrementally weighted root value of y up or down                   | IQRax              | x Increasing interquartile range up or down            |
| Rex                | x Upward rotated weighted square root                               | IQRay              | y Increasing interquartile range up or down            |
| Rwy                | y Upward rotated weighted square root                               | IQRaz              | z Increasing interquartile range up or down            |
| Rwz                | z Rotated upward weighted square root                               | IQRwx              | x Upward or downward rotating quartiles                |
| Dax                | Rotation sums of squares in the x-direction                         | IQRwz              | z Upward or downward rotating quartiles                |
| Day                | Rotation sums of squares in the y-direction                         | Stdax              | x Upward or downward incremental difference value      |
| Dwy                | y the squared difference in the direction of the upward translation | Stdwy              | y upward or downward rotational phase difference value |
| M X x              | The preferred solution for the downward direction of rotation of x  | Mp                 | pitch average  |
| Maxay              | The preferred solution for the y-down direction of rotation         | Mr                 | roll Mean  |
| Minay              | y upward or downward increasing inferior programs                   | My                 | yaw Mean   |
| Minwz              | z Inferior programs with upward or downward rotation                | Rp                 | pitch weighted root value                              |
| Sax                | x Increasing bias coefficients upwards or downwards                 | Rr                 | Roll weighted root value                               |
| Say                | y Increasing bias coefficients upwards or downwards                 | Ry                 | yaw weighted root value                                |
| Swx                | x Upward or downward rotational bias coefficients                   | Step               | pitch Difference                                       |
| Swy                | y Upward or downward rotational bias coefficients                   | Std                | roll Difference  |
| Swz                | z Upward or downward rotational bias coefficients                   | Stdy               | yaw Difference   |

Table 4.1: SVM algorithm mode parameter settings

| Optional parameter C |                    | kernel function (math.) |
|----------------------|--------------------|-------------------------|
| 1                    | $10^{-5}$          | Linear                  |
| 500                  | $5 \times 10^{-5}$ | Polynomial              |
| $10^3$               | $10^{-4}$          | RBF                     |
| $510^3$              | $510^{-4}$         | Sigmoid                 |
| $10^4$               | $10^{-3}$          |                         |
| $510^4$              | $510^{-3}$         |                         |

After data acquisition and data preprocessing, the process of pattern arithmetic in the soccer action recognition and evaluation system can be divided into three types: data division, pattern arithmetic, and classification, as shown in Figure 3.6.

**4. Experimental results and analysis.** In the action categorization experiment, two labels are set up: passing and shooting, which are represented by 0 and 1, respectively. 264 sets of passes and 250 sets of shots were obtained from the data collection experiments. In the action categorization experiment, two labels are set: pass type recognition and shot type recognition, and 0 and 1 are used to indicate the two categories. 264 sets of passes and 250 sets of shots were obtained from the data collection experiments. These datasets are divided into a training set in the recognition type and a test set in the recognition type according to the principle of randomness, of which 80% is used for the training type of recognition base. The results of the different parameter types set are shown in Table 3. Where the optional parameters C is from 1 to 50000, Y is from 0.00001 to 0.05, and the recognition types of the kernel function include Linear type, RBF type, Sigmoid type, and Polynomial category. To solve the overfitting problem, a 3-fold crossover was used. From the results, it is seen that the kernel function with C=1, Y of 0.0001, and Unitary type is used for the best pattern.

Then SVM-based classifiers are used to recognize shots and passes. Decision tree and KNN were chosen as the comparison algorithms for the experimental algorithms. Table 4 summarizes the accuracy of soccer action recognition. Among them, four methods, SVM+ Attitude Angle Pattern, SVM, KNNdecision tree and LDA have different accuracies with different parameters with maximum of 0.9,0.88,0.86 and 0.79 respectively.

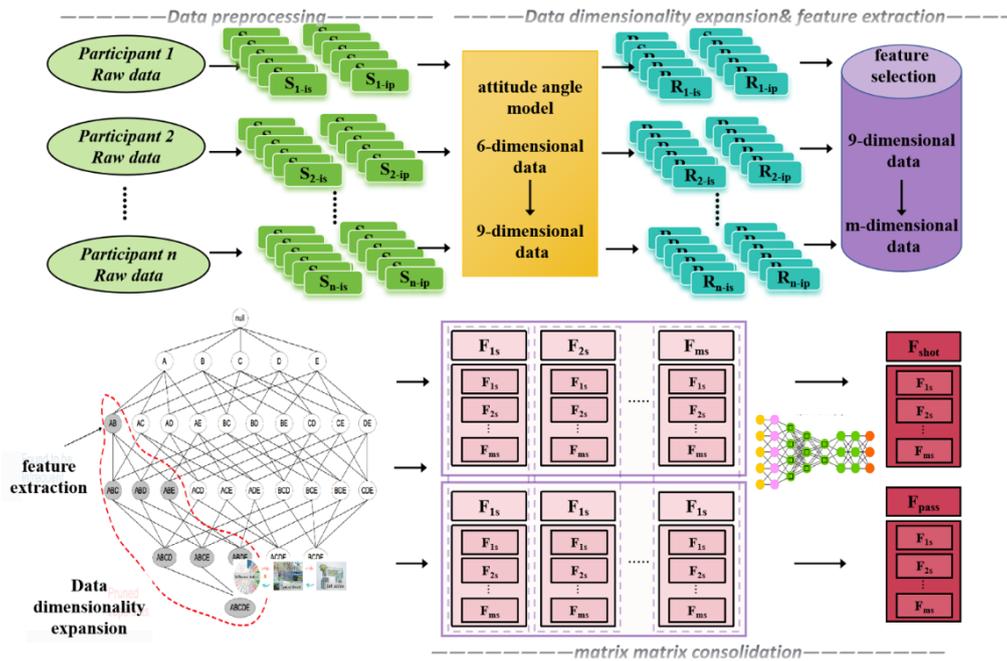


Fig. 3.5: Data processing process

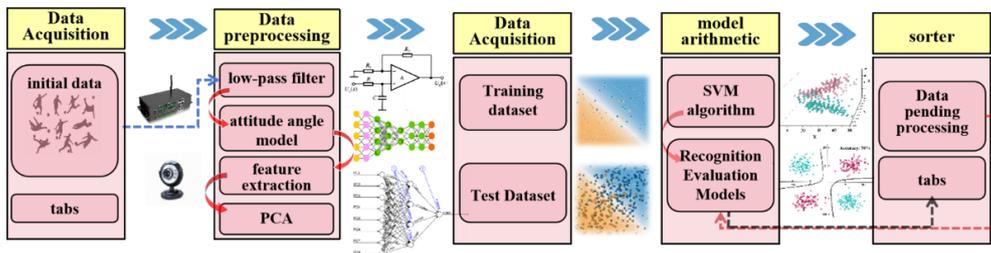


Fig. 3.6: Flow of soccer action recognition and evaluation system

It can be seen that the SVM-based algorithm chosen in this study has a better performance than the other comparative algorithms in all aspects combined. In addition, one of the algorithms with attitude angle pattern has better performance than the other algorithms as shown in Figure 4.1.

Figure 4.2 shows the experimental results of different algorithmic patterns for soccer training movement recognition and movement quality assessment. The SVM algorithm pattern based on the posture angular pattern recognizes passes and shots correctly to the extent of 85.7% and 88.5%, which indicates that there is a distinction between the passing and shooting action features. but the results of the SVM algorithmic pattern based on the posture angle pattern show that the degree of correctness, recall, and F1-score are better than the other algorithmic patterns, which indicates that the intelligent IoT type based on the SVM support vector-type recognition machine established in this paper has a significant improvement in the recognition rate in soccer training action recognition compared with the traditional algorithmic patterns. To improve the robustness of the framework to noise, measures such as data preprocessing, feature selection, algorithm optimization, and training strategies can be taken. These measures help to reduce the impact of noise on the recognition accuracy and thus improve the performance of the framework in practical applications.

Table 4.2: Comparison of results of different algorithmic modes for action recognition

| algorithmic model           | parameters                                       | rightness    |
|-----------------------------|--|--------------|
| SVM+ Attitude Angle Pattern | C=1<br>$\gamma = 10^{-5}$                        | 0.9          |
| SVM                         | $\gamma = 10^{-4}$<br>C=1                        | 0.88         |
| KNNdecision tree            | N_Neighbors=4 Min_Samples_Split=3<br>Max_Depth=6 | 0.85<br>0.86 |
| LDA                         | C=1<br>$\gamma = 10^{-5}$                        | 0.79         |

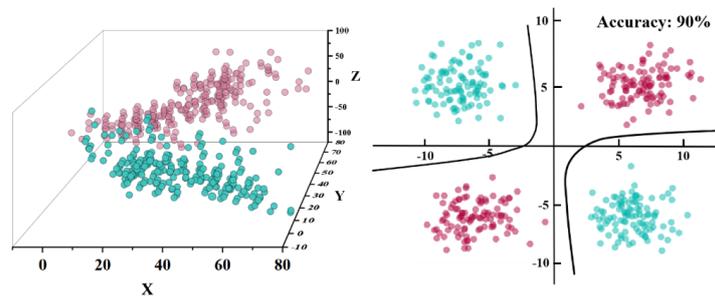


Fig. 4.1: Recognition results of soccer training movements based on SVM algorithm with posture angular pattern

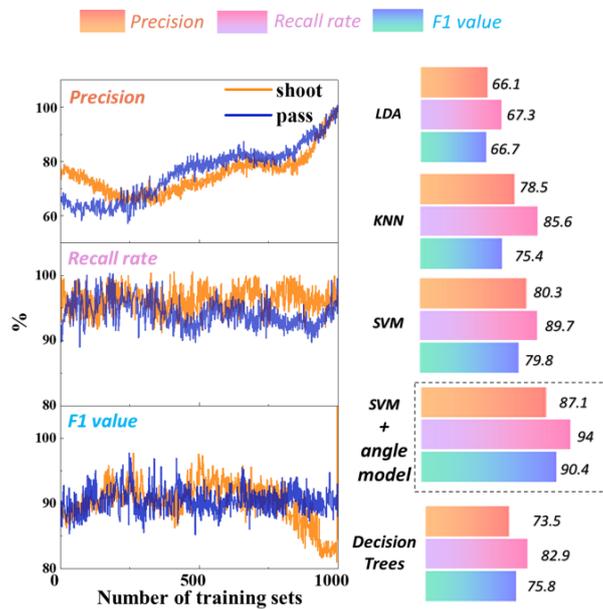


Fig. 4.2: Experimental results of different algorithmic models for soccer training movement recognition and movement quality assessment

**5. Conclusion and discussion.** The combination method of intelligent object type and support vector type recognition machine is used to recognize soccer training movements, and the designed data processing mode adopts posture angle pattern + SVM pattern classification algorithm to recognize different training movements. Through experiments, it is verified that the soccer training action recognition system based on attitude angle pattern + SVM has the highest recognition rate and the fastest computing speed, which significantly improves the performance over the traditional algorithm mode... The system allows for the migration change from an empirical type-driven approach to a data type-driven approach in the field of athletic training and, by extension, development to other applications of foot-based movement recognition and skill level assessment. In order to solve the problem of the framework's dependence on specific conditions or datasets, the following measures can be taken in the subsequent research: first, the framework is modularized to make it more versatile and extensible.

The method proposed in this paper combines attitude angle with SVM classification, which is efficient but at the same time has high computational complexity. The main challenges include real-time processing requirements and the efficiency of large-scale datasets. The application is promising, especially for scenarios such as soccer training movement analysis that require fast and accurate recognition. This makes it easy to replace or modify specific modules to adapt to different datasets and conditions. Second, migration learning and fine-tuning techniques are used when training the model to enable it to better adapt to specific tasks and data distributions. Finally, the framework is fully tested and validated to ensure its performance stability and reliability in different datasets and scenarios. Through these measures, the generalization problem of the framework can be effectively solved and its applicability in different real-world situations can be improved.

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