Recognition method of football players' shooting action based on Bayesian classification

Xiaofang Zhao

Department of Physical Education,
Dalian Maritime University,
Dalian 116026, China
Email: xiaofan@mls.sinanet.com

Abstract: Aiming at the problem of low accuracy and poor real-time performance of existing algorithms in the process of football players' shooting action recognition, a football players' shooting action recognition method based on Bayesian classification is proposed. Firstly, Gaussian mixture model is constructed to extract the characteristics of shooting action. Secondly, the Gaussian parameters are estimated to obtain the optimal state sequence, which provides a basic reference for football players' shooting action recognition. Finally, based on the marking of football players' shooting action behaviour, the recognition of football players' shooting action based on Bayesian classification is realised. Experiments show that the designed Bayesian classification method can accurately identify the shooting action of football players, and has good real-time performance. This shows that the design method can provide basic basis and theoretical guarantee for football players' action recognition, and has certain practical application performance.

Keywords: Bayesian method; motion recognition; football sport; athlete movement.

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Biographical notes: Xiaofang Zhao graduated from the College of Physical Education and Sports of Beijing Normal University in July 2009, majoring in Sports Training. In June of 2012, she graduated from the School of Physical Education and Sports of Beijing Normal University with a Master's in Physical Education and Training. She is now a Lecturer in the Physical Education Department of Dalian Maritime University. Her research direction is physical education and training.

1 Introduction

In football matches, the players' movement is a collective action of many people, with a high degree of synergy. The cognition and recognition of group behaviour has always been an important subject of computer vision. It is widely used in image monitoring, target image summary, human-computer interaction, motion image analysis, motion assisted training, competition assisted referee and image query (Yuan et al., 2021; Hendricks et al., 2020). Therefore, the identification of shooting action of multiple players in football match is conducive to improve the training effect of football players. The recognition of shooting action in football matches includes feature extraction (Rathnamala and Jenicka, 2021; Taguchi and Turki, 2021), object tracking and detection (Fang et al., 2020; Zhou et al., 2020), action expression (Damotharasamy, 2020), classification methods and behaviour recognition, including the detection, segmentation, tracking and identification, semantic expression and inference of moving objects, as well as the application of model recognition, image processing, drawing and so on. Accurate recognition of football players' shooting actions can help improve players' shooting skills and improve the level of football players.

At present, there is no specific research content on shooting action recognition of football players, but some scholars have studied the action recognition method of human movement behaviour. Vasconez et al. (2021) studied a recognition system based on the attitude semantic information of combined objects, using convolution 2D attitude estimation methods to form RGB static images and normalise feature vectors to identify possible future actions predicted by human activities, thereby increasing staff productivity. Li et al. (2021) use depth information to reconstruct 3D point cloud, use time pyramid to segment time series of different scales, and stitch the features of each time period, so as to show the spatial distribution of the point cloud of the main moving parts of the human body, and identify the human behaviour features according to the track of historical point cloud. Athavale et al. (2021) puts forward the pre-training CNN model of SVM classifier, uses VGG16 to classify the signals of human activities, constructs the sample data set of human activities in daily life, and uses the CNN model to feedback the depth characteristic information to complete the recognition of human motion. Although the above methods can recognise human motion, there is still a problem of insufficient recognition accuracy for the recognition of shooting.

In order to improve the recognition accuracy of football players' shooting action, this paper proposes a football players' shooting action recognition method based on Bayesian classification. The specific architecture is as follows:

1 A Gaussian mixture model with a mixture of components is constructed, and the Gaussian mixture model is used to extract the shooting behaviour characteristics of football players, including spatial position characteristics and motion characteristics.

2 When the likelihood function reaches the maximum value under the parameters of Gaussian model, the algorithm is used to estimate the parameters of Gaussian model to determine the optimal state sequence of football players' shooting behaviour data.

3 Mark the behaviour characteristics of football players' shooting action, and use the Bayesian classification method to realise the effective recognition of football players' shooting action.

4 The performance of the design method is verified by experiments and compared with the methods in the literature.

2 Detection method of shooting action characteristics of football players

2.1 Feature extraction of shooting action based on Gaussian mixture model

In order to accurately detect the shooting action of football players, Gaussian model needs to be used to extract the characteristics of sports behaviour.

The continuous motion of human body can be divided into several states; each state is composed of several parts of the body. The spatial position feature f_{CC} and the motion feature C are both regarded as Gaussian mixed model (Avila et al., 2021). A Gaussian mixture model containing M mixtures is represented as follows:

$$p(O_t) = \sum_{x=1}^{M} w_x N_x (O_t; \mu_a, \Sigma_x) \tag{1}$$

Among them, w_x, μ_x and Σ_x represent respectively the weighting coefficient, mean and covariance of the λ mixture (Adimurthi et al., 2021). The Gaussian mixed model λ can be expressed as:

$$\lambda = \{w_x, \mu_x, \Sigma_x\}, x = 1, 2, ..., M \tag{2}$$

The characteristics of the shooting action of football players are as follows:

$$A(t) = (f_{CC} + f_{CD}) \sum_{t=1} (M_{2,t} - M_{1,t})(S_{t+1} - S_t)(O_{2,1} - O_{1,t}) \tag{3}$$

Spatial characteristics (Yu et al., 2021) f_{CC} and motion characteristics f_{CD} contain M_1 and M_2, respectively. The parameters S_t and S_{t+1} represent the state of t time and $t + 1$ time respectively; the parameters $M_{1,t}$ and $M_{2,t}$ represent the number of mixed components contained in f_{CC} and f_{cp} of t time respectively; the parameters $O_{1,t}$ and $O_{2,t}$ represent the observation of t time respectively, that is, the characteristics of spatial position f_{CC} and the characteristics of motion f_{CD}.

2.2 Gaussian parameter estimation and optimal state sequence extraction

According to the extraction results of shooting behaviour characteristics of football players, Gaussian parameter estimation and optimal state sequence extraction are carried out.

For a certain action, the state set is $e = \{e_1, e_2, \cdots, e_N\}$, if the state of t moment is s_t, then the observation sequence of $s \in \{e_1, e_2, \cdots, e_N\}$, t moment is $O_t = (O_{1,t}, O_{2,t})$, the observation sequence of f_{cc} is $O_1 = (O_{1,1}, O_{1,2}, \cdots, O_{1,T})$, and the observation sequence of $\mathrm{f_{cp}}$ is $O_2 = (O_{2,1}, O_{2,2}, \cdots,)$.

Define initial state probability as π_x:

$$\pi_x = p(s_1 = e_x) 1 \le x \le N \tag{4}$$

The state transition probability distribution is defined as $A = \{a_{xy}\}$, where a_{xy} represents the probability of changing from state x to state y (Jing et al., 2021).

$$a_{xy} = p(s_{t+1} = e_x | s_t = e_x), 1 \le x, y \le N \tag{5}$$

The observed probability distribution is defined as $B = \{b_t(x)\}$, in which $b_t(x)$ represents the probability of O_t when the state of the t moment is x.

$$b_t(x) = \left[\sum_{m=1}^{M_{1,t}} w_{1,m}^x N\left(O_{1,t}; \mu_{1,m}^x, \sum_{1,m}^x\right)\right]\left[\sum_{m=1}^{M_{2,t}} w_{2,m}^x N\left(O_{2,t}; \mu_{2,m}^x, \sum_{2,m}^{xi}\right)\right] \tag{6}$$

Among them, the parameters $w_{1,m}^x$, $\mu_{1,m}^x$, and $\sum_{1,m}^x$ represent the weighting coefficient, mean value and covariance of the mixed components of the m in the $O_{1,t}$ Gaussian mixed model, while $w_{1,m}^x$, $\mu_{1,m}^x$, and $\sum_{1,m}^x$ represent the weighting coefficient, mean value and covariance of the mixed components of the m in the $O_{2,t}$ Gaussian mixed model. Assume that the set of parameters in the model is $\theta = \{A, B, \pi\}$.

For the feature f_{CC} of space position, the parameter learning process of Gaussian mixture model is to determine the Gaussian parameter λ_1 according to the likelihood function of the feature sequence, and make the maximum value of the likelihood function under the parameter λ_1, namely:

$$\lambda_1 = \arg\max p(O_1 | \lambda_1) \tag{7}$$

Among them, $\lambda_1 = \{w_{1x}, \mu_{1x}, \Sigma_{1x}\}$, $x = 1, 2, \cdots, M$ is the set of Gaussian parameters corresponding to f_{CC}.

EM algorithm (Asheri et al., 2021) is used to estimate Gaussian parameters. The process can be divided into *E* and *M* steps.

- *E step:* using the estimated $w_{1,x}$, $\mu_{1,x}$, Σ_{1x} from the previous iteration, find the probability that the $O_{1,t}$ will be generated by the x mixture:

$$\alpha_1(t, x) = \frac{w_{1,x} N\left(O_{1,t}; \mu_{1,x}, \Sigma_{1,x}\right)}{\sum_{y=1}^{m} w_{1,y} N\left(O_{1,t}; \mu_{1,y}, \Sigma_{1,y}\right)} \tag{8}$$

- *M step:* the $\alpha_1(1, x)$, $\alpha_2(2, x)$, $\cdots$, $\alpha_1(\mathrm{T}, x)$ derived from E step calculates the parameter estimates for the x mixture.

$$\hat{w}_{1,x} = N_{1,i} / T \tag{9}$$

$$\hat{u}_{1,x} = \frac{\sum_{t=1}^{T} \alpha_1(t, x)}{N_{1,x}} \tag{10}$$

$$\widehat{\sum}_{1,x} = \frac{\sum_{t=1}^{T} \alpha_1(t, x)}{N_{1,x}} \cdot \left(O_{1,t} - \mu_{1,x}\right) \cdot \left(O_{1,t} - \mu_{1,x}\right)^T \tag{11}$$

Of which, $N_{1,x} = \sum_{t=1}^{T} \alpha_1(t, x)$.

The learning process of Gaussian parameters corresponding to the motion feature f_{CD} is also estimated by *EM* algorithm. Get all the parameters of Gaussian model, and then calculate the observation probability matrix (Braca et al., 2020). To find the best sequence of states, use the Viterbi algorithm as follows:

Firstly, an auxiliary variable $\delta_{t+1}(x)$ is defined to represent the θ of the given model and the O of the observed sequence, and the $s_1 s_2 \cdots s_t$, $\delta_{t+1}(x)$ of the state sequence with the highest probability of s_t under the state e_x is used.

$$\delta_{t+1}(x) = \max p\left(s_1 s_2 \cdots s_t = e_x, O_1 O_2 \cdots O_t \mid \lambda\right) \tag{12}$$

Initialisation parameters:

$$\delta_1(x) = \pi_x b_x\left(O_1\right), 1 \le x \le N, \left(\psi_1(x) = 0\right) \tag{13}$$

Recursive process:

$$\begin{gathered} \delta_1(y) = \max_{1 \le x \le N}\left[\delta_{t-1}(x) a_{xy}\right] b_x\left(O_t\right) \\ 2 \le t \le T, 1 \le y \le N \end{gathered} \tag{14}$$

$$\psi_1(y) = \arg\max\left[\delta_{t-1}(x) a_{xy}\, 2 \le t \le T, 1 \le y \le N\right] \tag{15}$$

Define the following two parameters:

$$P^* = \max_{1 \le x \le N}\left[\delta_T(x)\right] \tag{16}$$

$$S_T^* = \arg\max_{1 \le x \le N}\left[\delta_T(x)\right] \tag{17}$$

Then the optimal sequence of states obtained is as follows:

$$S_T^* = \psi_{t+1}\left(S_{T+1}^*\right) t = T-1, T-2 \cdots, 1 \tag{18}$$

3 Identification of shooting action of football players based on Bayesian classification

3.1 Behaviour markers of football players' shooting action

Suppose the set of training samples of shooting action image is $(x_1, y_1), \cdots (x_i, y_i), \cdots (x_N, y_N)$, in which x_i represents the sample data of shooting action image and y_i represents the sample mark of shooting action image (Yuan, 2020; Liu and Dong, 2021). In the training sample N, randomly selecting the shooting action sample data as the known sample, using the AdaBoost algorithm (Ciaburro, 2021) as the weak classifier, obtaining the assumptions of the training sample, taking the $\varphi(Y, h, X)$ as the basis, calculating the error rate of the shooting action image sample, and obtaining:

$$\varepsilon_1 = \frac{\sigma(Y, h, X) \times \left(h_t\left(x_i\right) \ne y_i\right)}{\left(x_1, y_1\right), \cdots \left(x_i, y_i\right), \cdots \left(x_N, y_N\right)} \tag{19}$$

where ε_1 represents the sample error rate.

Based on the calculation results of formula (19), the extracted shooting action characteristics shall be marked as 1, and the others as –1. Through the iterative construction of the football player shooting action characteristic mark model, the model is represented as:

$$\hat{C}_i = \arg\min \left\| d_i - C\left(d_j\right)^2 \right\| * \varepsilon_1 \tag{20}$$

Among them, d_i represents the i feature data of the shooting action sequence, and $C(d_j)$ represents the j feature data of the training sample.

In accordance with the formula (20), the characteristics of shooting action of football players shall be marked.

3.2 Recognition of football players' shooting behaviour based on naive Bayes

Using the existing data to build a classifier based on shooting action features, we can create the most suitable category marks for specific features. Simple Bayesian classifier is a simple random classification method based on Bayesian theory. It assumes that each attribute is not related to other attributes, and uses the combination of known probability and known classified case probability to obtain the type with the largest a posteriori probability and judge the uncertainty (Angadi et al., 2021).

It is assumed that the shooting action of soccer players can be represented by a set of instance attribute characteristic values $\langle a_1, a_2, \cdots, a_m\rangle$, and the most probable category marker $c(x)$ can be found when the x of a feature is given. Through the maximum posteriori assumption, the following can be derived:

$$c(x) = \arg\max_{c \in C} P\left(c \middle| a_1, a_2, \cdots a_m\right) \tag{21}$$

The basis of naive Bayes classification is to separate the values of each attribute independently in a given target.

Under this standalone form, the formula (21) is rewritten as a Bayesian equation:

$$c(x) = \arg\max_{c \in C} P(c) \prod_{j=1}^{m} P\left(a_1 \mid c\right) \tag{22}$$

Although in practice, Bayesian presupposition is often not used correctly, but in this case, naive Bayesian classifier still shows a strong efficiency, so it has been applied in classification, clustering and pattern selection.

Among them: $P(c)$ represents the prior probability of c, $P(a_y| \ c)$ is in a set, through the various types and characteristics of the combination of calculations and estimates.

Using the threshold recognition algorithm (Pan et al., 2021), the shooting behaviour of football players is discriminated according to the motion images, and the potential of the motion behaviour is established, which can lay a good foundation for the recognition of the action. In football matches, there are a lot of complicated situations, which make the sports of the athletes present a more complicated scene. In order to realise the efficient recognition of motion images, this paper uses threshold recognition algorithm to identify the shooting motion. The process includes:

Step 1 The image pixel value is N_e, the setting matrix coordinates are: $A(x_1, y_1)$, $B(x_2, y_2)$, $C(x_3, y_3)$, $D(x_4, y_4)$, and the coordinate matrix is:

$$\begin{cases} P = \left(x_2 - x_1\right) / \left(y_3 - y_1\right) \\ S = \left(x_2 - x_1\right) * \left(y_3 - y_1\right) \end{cases} \tag{23}$$

Step 2 When the pixel value of the image is larger than the recognition threshold A, the shooting action features can be extracted.

Step 3 If no pixel is specified, the coordinates are corrected and expanded.

Step 4 Complete the scan, get the N_e and confirm the target.

Step 5 Compare the recognition threshold, when $|1 - P|$ is less than A, get the image area.

Step 6 Through the target area, calculate the area to the image area ratio: $M = N_e / S$, $|0.785 - M| < A$, then automatically identify the football player shooting action.

Step 7 Output shooting action results.

4 Experimental verification

4.1 Experimental data and scheme

- Experimental data: this experiment collects football players' game video images, sets sampling every five frames, and compares the coordinate information obtained last time with the current coordinate. If the position of the coordinate point changes on a critical point for five seconds, the position will be regarded as stopped, then the data of the position will be extracted and recorded, and finally the position information will be stored.
- Experimental scheme: select 14 eigenvalues of five nodes, take the recognition time, recognition accuracy and recall as the experimental comparison index, and compare the Bayesian classification method proposed in this paper with the methods in the literature to verify the specific performance of the proposed method.

4.2 Comparison of shooting action recognition time of football players

In order to verify the efficiency of the algorithm, the time of shooting action recognition of soccer players is used as a verification index to compare. The shorter the recognition time is, the higher the efficiency of shooting action recognition is. By comparing the methods of Vasconez et al. (2021) and Li et al. (2021) and the proposed method, it is found that the recognition time of shooting action of soccer players with different methods is shown in Table 1.

Table 1 Comparison of recognition time for different methods

Training sample data/ groups	*Proposed method/s*	*Reference (Vasconez et al., 2021) methodology/s*	*Reference (Li et al., 2021) methodology/s*
100	1.6	8.1	6.8
200	2.9	10.6	14.5
300	3.2	13.6	18.9
400	4.1	17.8	20.3
500	6.2	19.7	22.5

According to Table 1, with the increase of training sample data, the shooting action recognition time of football players with different methods increases. When the training sample data is 500 groups, the recognition time of football players' shooting action of reference (Vasconez et al., 2021) method is 19.7 s, the recognition time of football players' shooting action of reference (Li et al., 2021) method is 22.5 s, while the recognition time of football players' shooting action of the proposed method is only 6.2 s. It can be seen that the football player shooting action recognition time of the proposed method is short; indicating that the football player shooting action recognition time efficiency of the proposed method is high.

Table 2 Comparison of accuracy of shooting action recognition of football players

Shooting action	*Proposed method*		*Reference (Vasconez et al. (2021) methodology*		*Reference (Li et al. (2021) methodology*	
	Correctly identify quantity	*Accuracy/%*	*Correctly identify quantity*	*Accuracy/%*	*Correctly identify quantity*	*Accuracy/%*
Arching of the foot	36	96	33	90	31	87
Bigfoot sling	27	98	25	94	25	94
Instep volley	42	96	41	90	38	86
Volley of instep	51	94	48	92	47	90
Volley shot from the instep	48	96	45	90	42	87

4.3 *Comparison of accuracy of shooting action recognition of football players*

Recognition accuracy is one of the main indexes of recognition method. In order to verify the recognition effect of soccer players shooting action, the recognition accuracy of soccer players shooting action is compared. The higher the accuracy, the better the recognition effect. On the contrary, the lower the accuracy, the worse the identification effect and the method has no practical application performance. In this paper, the different shooting actions in the video of soccer match are used as recognition objects, and the recognition accuracy is compared with the results shown in Table 2.

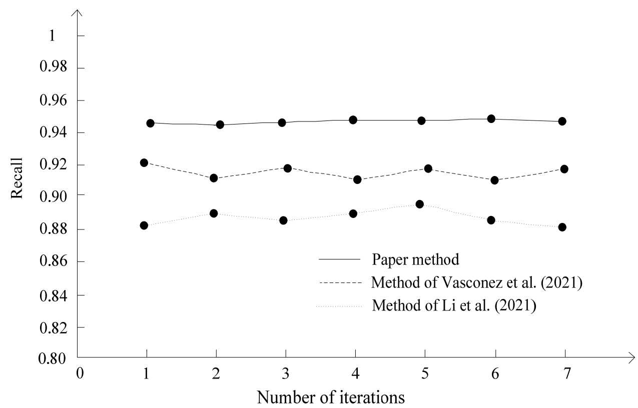
It can be seen from Table 2 that for different shooting actions, the methods proposed in this paper can effectively identify, and the number of correct identification is always higher than that of Vasconez et al. (2021) and Li et al. (2021), and its average accurate recognition rate is more than 95%, indicating that the method proposed in this paper has high practical application performance and can obtain accurate football players' shooting action recognition results.

4.4 *Comparison of recall rate of shooting action recognition among football players*

Recall rate refers to the shooting action information data of football players recognised within the specified time, which can measure the recall rate of algorithm recognition. The higher the recall rate, the better the effect of the method. It is a main index used to evaluate the recognition algorithm. Taking the recall rate as the index, the superiority of this method is verified by comparing the recall rate of this method with that of Vasconez et al. (2021) and Li et al. (2021). The results are shown in Figure 1.

It can be seen from the comparison results of recall rate that the recall rate of this method is high, and it is always better than Vasconez et al. (2021) method and Li et al. (2021) method, indicating that this method has a high recall rate in the process of football players' shooting action recognition. Combined with the accuracy comparison results in Table 2, it can be seen that this method can maintain high accuracy and has good recall, which further verifies the practical application performance of the proposed method.

Figure 1 Comparison of recall rates for different methods



5 Conclusions

In order to solve the problem of low accuracy and poor real-time performance in the process of shooting action recognition, a method of shooting action recognition based on Bayesian classification is proposed. Based on the Gaussian hybrid model, the shooting action features of soccer players including spatial position features and motion features are extracted. After Gaussian parameters are estimated and the optimal state sequence is obtained, the Bayesian classification is used to recognise the shooting action of soccer players. Experiments show that the method proposed in this paper can accurately recognise the shooting action of soccer players and has good real-time performance. Experimental results show that the proposed method has good practical performance, and it can provide the basis and theoretical guarantee for the action recognition of soccer players and other aspects of video image.

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