

Retraction

Retracted: Feature Extraction of Foul Action of Football Players Based on Machine Vision

Mobile Information Systems

Received 31 October 2023; Accepted 31 October 2023; Published 1 November 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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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.

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- [1] H. Guan and H. Niu, "Feature Extraction of Foul Action of Football Players Based on Machine Vision," *Mobile Information Systems*, vol. 2022, Article ID 7253159, 6 pages, 2022.

Research Article

Feature Extraction of Foul Action of Football Players Based on Machine Vision

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Received 1 December 2021; Revised 17 December 2021; Accepted 27 December 2021; Published 31 January 2022

Academic Editor: Hasan Ali Khattak

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With the improvement of technology and tactics, the rhythm of football match is getting faster and faster, which leads to more intense competition behavior in a football match; the physical contact of both players is also increasing, and the frequency of fouls by football players is getting higher and higher. This leads to fouls by players. Because of the error of visual analysis, in the crowd of high-level football players, the traditional football players' foul behavior feature extraction method has the problem of low precision of foul action feature extraction. This paper mainly studies the feature extraction of soccer players' foul action based on machine vision. To solve these problems, this paper uses a machine vision-based football player foul action feature extraction method, using a machine vision system to obtain football player action image, based on threshold recognition algorithm to identify the football player's foul action. Based on the recognition of the foul action image, the potential function sequence of the foul action sequence is established by the Harris 3D operator, and the characteristic data of football player foul action are filtered by the AdaBoost algorithm. The simulation results show that this method has high accuracy in identifying fouls in the range of high-level football players and effectively reduces the recognition error. The method proposed in this paper can effectively analyze the characteristics of foul action and help football clubs to develop more perfect tactics.

1. Introduction

In the process of frequent fouls in football matches, in order to ensure the safety of football players and make them play at the highest level, FIFA constantly modifies and consummates the rules of football matches. The increase of football match intensity brings great challenges to the judgment of referees.

The study of feature extraction of foul action of football players based on machine vision has attracted the interest of many experts and has been studied by many teams. For example, some teams found that in the analysis of the characteristics of direct free kick foul in the final stage of the 17th World Cup, the land run analyzed the foul position and regional characteristics of direct free-kick, and considered that the fouls in contemporary football matches were mainly direct free-kick fouls, all of which were dominated by lower

limb fouls, in which fouls were mostly tripped, followed by push, pull, and kick. Direct free-kick fouls are the most common in midfield, especially near midfield, in front of the back, and in the front, fouls are more frequent [1]. A comparative study of the foul characteristics of Zuo Hao-chang in the 2010 and 2006 World Cup finals shows that the number of fouls in the 2006 World Cup team is significantly higher than that in the 2010 World Cup. By comparing and analyzing the total number of fouls in the last three World Cup teams, the number of fouls is reduced year by year. The number of fouls in the game is obviously related to the final result, and the team with good fouls is less than the team with poor fouls [2, 3]. By analyzing the 2004 European Cup players' fouls, some teams found that the 2004 European Cup foul exceeded the first half in the second half of the year because of the lack of physical reserves in the second half of the game and the score gap. According to the statistics of

fouls, European players have more fouls on upper limbs than lower limbs [4]. A statistical study of the foul characteristics of players in the 2004 Asian Cup and the European Cup of the same year, found that in today's football match, players in Europe and Asia were more active in terms of foul motivation. There are worse fouls and offensive fouls [5]. During the first half and the second half of the game, there was a high incidence of fouls. The study found that in the above two periods, the player's mentality changed a lot. In the second half of the second half, due to the decline in physical fitness and the gap in the field score, it was easier to foul [6]. Common features of the two cup games are that the second half has more red and yellow cards than the first half. The penalty area is characterized by the largest number of fouls in the Eurasian midfield, a similar number of fouls by the forward players, more fouls in the backcourt of the Asian Cup, more fouls in the frontcourt of the European Cup. Finally, European fouls on upper limbs exceed lower limbs, most of which are push and tripping. Asian fouls on lower limbs are more than upper limbs, focusing on pulling fouls and kicking [7]. Although their research results are very rich, there are still some shortcomings.

The purpose of this paper is to understand the foul characteristics of male and female players in high-level football matches in the world and to provide a theoretical reference for our male and female athletes and coaches to learn about the foul characteristics of powerful teams in the world. At the same time, it provides a theoretical reference for men and women referees at all levels to understand and study the foul characteristics of high level and strong teams in the world, to improve the professional level of referees at all levels, to pay attention to the differences between men and women in the future competition law enforcement, to ensure the smooth progress of the competition, and to promote the normal play of the skills and tactics of both athletes.

2. Method

2.1. Foul Action Recognition. Based on the action image of the football player, the threshold recognition algorithm is used to identify the foul behavior of the football player, and to prepare for the establishment of the sequence potential function of the foul action. The more complicated situation will appear in a football match, which leads to the complex background of the player's action picture. Therefore, the threshold recognition algorithm is used to identify the foul action. It is assumed that the number of effective pixels in the action image is n_e , the action image is a matrix, and the coordinates of four points are $A(x_1, y_1)$, $b(x_2, y_2)$, $c(x_3, y_3)$, and $d(x_4, y_4)$. The formulas for calculating the parameters P and S are shown below [8].

$$P = \frac{(x_2 - x_1)}{(y_3 - y_1)}, \quad (1)$$

$$S = (x_2 - x_1) * (y_3 - y_1). \quad (2)$$

2.2. Establishment of the Preorder Potential Function for Foul Action. Using foul action to identify results, the Harris 3D operator establishes a sequence potential function for foul action, provides support for feature extraction of foul action. Harris3D operator is used to mine foul movements, extract the temporal and spatial interest points for each different foul action in the image, the features of gradient histogram and towline direct graph are obtained, divided into 72 and 90 dimensions, fusion gradient histogram, and flow direction histogram, get a 162-dimensional eigenvector, this is a potential feature of foul behavior. The key point of choosing a football player, e.g. (x_{zi}, y_{zi}) , according to the structural characteristics of the human body, the body of a football player is divided into seven local reference points: shoulder, left and right arm, left and right leg, left and right foot, for example (a_i, b_i) , n represents a local reference center, it is called a point of interest, seven regions based on local reference points; (x_j) and (y_j) represents each point of interest in time and space [9].

$$n = \frac{\operatorname{argmin} \sqrt{(a_i - x_j)^2 + (b_i - y_j)^2}}{(x_{zi}, y_{zi})}. \quad (3)$$

2.3. Feature Extraction of Foul Action. On the basis of the sequence potential function, the feature data of football players' foul behavior are screened by enhancement algorithm, and the feature extraction of training and identifying football players' foul behavior is realized. Suppose football player fouls, the action image training sample set is $(x_1, y_1) \dots (x_i, y_i) \dots (x_n, y_n)$, where x_i denotes foul action image sample data, y_i denotes foul action image sample mark. The sample data of any foul action in the training sample N are used as known samples. The AdaBoost algorithm is a weak classifier, and the training sample is obtained. Suppose, based on $\phi(y, h, x)$, the sample error rate of the football player's foul action image is calculated, and formula (4) is obtained, where, ϵ_t represents the sample error rate [10].

$$\epsilon_t = \frac{\phi(Y, h, X) \times (h_t(x_i) \neq y_i)}{(x_1, y_1), \dots (x_i, y_i), \dots (x_N, y_N)}. \quad (4)$$

According to the calculation results of formula (4), the features of the extracted foul action are marked as 1, and the rest are marked as -1. By the iterative method, the feature extraction model of football player's foul behavior is established. The representation of the model is as follows [11]:

$$\hat{C}_i = \operatorname{argmin} \|d_i - C(d_j)\|^2 * \epsilon_i. \quad (5)$$

The d_i represents the i feature data in the foul action sequence, and the $C(d_j)$ represents the category of the foul action feature data in the training sample. According to formula (5), the feature extraction of the behavior of football players based on machine vision is realized.

2.4. Establishment of Membership Matrix. Clustering bottom foul action features using K -mean, K , for cluster centers get

$K \times 162$ -dimension foul action image, at the same time generate three levels and seven areas of foul action images, each area foul action T frame is defined as the space-time foul action module, represents the characteristics of a part of a football player's foul behavior. When the foul action image unit of two overlapping $T/2$ frames are connected, all the action units in each foul action image are organically synthesized, a series of temporal and spatial foul action units with length, after k -mean clustering, the characteristics of the echo bow of the action-image measured by the foul action data set are obtained as formula (6), where f_p represents the BOW features of foul action image p echo, Kn indicates the number of cluster centers in the foul range, and N represents the sequence length of the temporal and spatial units of the foul action image [12].

$$f_p = \frac{K_n \times N}{K} * \frac{K \times 162}{P}. \quad (6)$$

The fusion formula is BOW, where F_p represents the fusion characteristics of each region at the corresponding level.

$$F_p = \sum_{n \in [1,7]} K_n \times N. \quad (7)$$

3. Experiment

3.1. Experimental Data Sources. There are more than 200 papers on "athlete foul, soccer player foul", and more than 20 studies on the foul characteristics of men's, including 3 excellent master's papers and 9 studies on the foul characteristics of female football players, including 1 excellent master's thesis. However, there are few articles on the foul characteristics of male and female athletes. Therefore, this paper takes male and female athletes as the research object.

3.2. Experimental Design. This paper studies the foul characteristics of high-level athletes by means of literature, investigation, video observation, data statistics, and other scientific research methods through the technical statistical research on 57 fouls of women's World Cup and 32 football teams in the European Cup.

4. Result

4.1. Analysis of the Time Period When Male and Female Athletes Get Red and Yellow Cards. As can be seen from Figure 1, the number of yellow cards obtained by male athletes in the fourth phase is up to 33, accounting for 28.45% of the total number of yellow cards. Continue to compete fiercely in the game, hoping to open the score as soon as possible to grasp the initiative. As shown in Figure 1, the peak of the red card appears in the last 15 min, indicating that the team athletes at all costs to achieve a victory or equal share, the psychology of winning and losing makes them use fierce, aggressive, and harmful defensive actions to prevent the other side from threatening attacks, even if the foul player is sent off by the referee to show the red card, it is

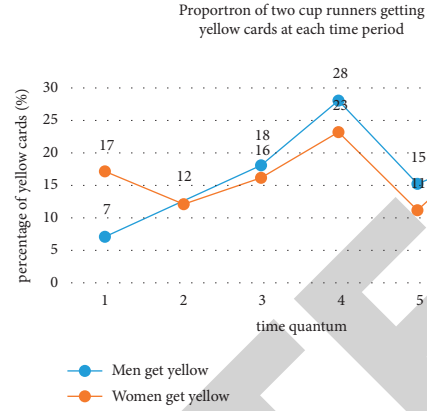


FIGURE 1: The proportion of red and yellow cards obtained by athletes in two cup tournaments in each time period.

difficult for the other side to make full use of the increasing advantages of the game.

4.2. Regional Analysis of Red and Yellow Cards for Athletes from Different Positions of Men and Women. Figure 2 shows that the men's forward and the guard gets 7 and 14 yellow cards in the midfield, 35% and 38.88%, respectively; the front and back of the avant-garde have 10 yellow cards and 17 yellow cards, accounting for 17.54% and 26.32% of the total number of yellow cards received by the avant-garde, which indicates that the defensive area of the men's forward and the guard is expanding, not just in your own area. The vanguard and the guard can go to the midfield to assist the vanguard to launch the fierce robbery together, the avant-garde team can cooperate with the forward team, so that the other side cannot pass easily, return to the backcourt area to help the guard set up the defense line, ensure that the target will not be lost.

4.3. Analysis of Foul Time Periods for Male and Female Athletes. We can see from Figure 3 that the first, fourth, and sixth line breaking chart of the male foot athletes foul time all points are in the peak position, showing a gradual upward trend, these three points are the first 15 min of the upper and lower half, and the last 15 min which is close to the end of the game is the best time for players to foul.

The number of fouls in the first stage accounts for 17.43% of the total number of fouls. On the one hand, this shows that the top 15 athletes want to use their rich physical strength to exert their technical and tactical advantages, restrain their opponents' skills and tactics, win active goals and win psychological advantages; on the other hand, as the law enforcers of the game, in order to better control and guide the game, the referee is more strict in the first 15 min, the start of the game, resulting in more first-half fouls in the first 15 min. The number of fouls in the fourth stage was 18.27, because the coach made tactical arrangements and adjustments in the second half, and the player recovered in the 15 min of midfield, so the players were more intense in the first 15 min of the second half and fought frequently,

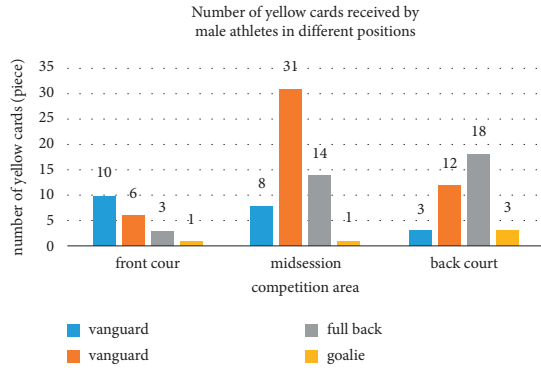


FIGURE 2: The number of yellow cards obtained by athletes in different positions of men and women.

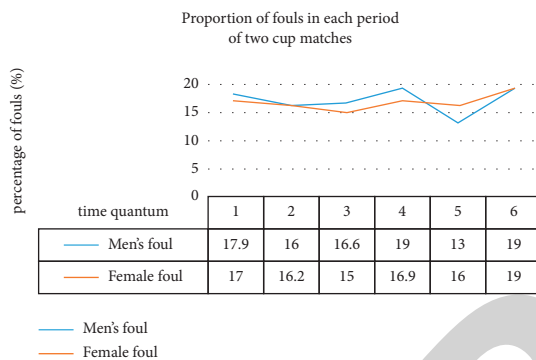


FIGURE 3: The proportion of fouls in each period of the two cup matches.

want to open up or win. The number of fouls in the sixth stage reached 19.01 because the last 15 min of the second half was the key stage of the game, the score could be rewritten in the last 15 min, the leading team wanted to keep the advantage and win the game, and when the last 15 min of the game fell, the defense slowed down.

4.4. Analysis of Foul Types of Male and Female Athletes. Table 1 and Figure 4 show the proportion of foul types for women's World Cup players in 2019. The way in which women footballers kick, push, grab, stumble, collide, and pull, account for 83.86% of the total number of fouls. One of the most serious fouls is playing or trying, there were 102 fouls, which is 18.72% of the total fouls, the second is to push and intercept each other which is 15.78%, trips account for 14.5%, collisions account for 10.83%, and pull each other accounts for 8.62%.

From the video game of the Women's World Cup, it can be found that the speed and strength of players on the field compared with the last World Cup, especially in Germany, Brazil, and the United States, the physical fitness of athletes close to men's football players, especially in close defense players, the ability to use body fighting and robbery increases the proportion of collisions and tripping fouls. From the analysis of defensive technology, the technique of snatching the ball is mainly done by the lower limbs, and the foul

TABLE 1: Statistics on the types of fouls committed by athletes in the final stage of the Women's World Cup 2019.

Type of foul	Number of fouls	Percentage (%)
Deliberate handball	20	3.67
Beat or attempt to beat	0	0
Pull each other	47	8.62
Push an opponent	86	15.78
Jump to each other (goalkeeper)	45	8.25
Obstruction (goalkeeper)	11	2.02
Grabbing each other	86	15.78
Trip or attempt to stumble	79	14.5
Kick or attempt to kick	102	18.72
Spit on each other	0	0
Action is dangerous	10	1.83
Fake a fall	0	0
Hit the other side	59	10.83
Amount to	545	100

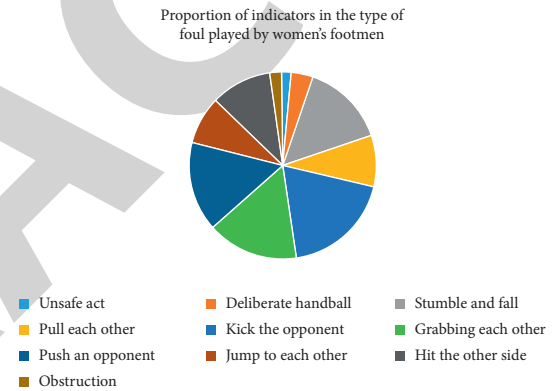


FIGURE 4: Percentage of indicators in the type of foul played by women football players.

action in the process of snatching the ball should be mainly kicking, tripping, and snatching the other side. These fouls are offensive and can directly make the hitter fall and lose control and can play the purpose of preventing the other side from attacking. Due to the improvement of the statistical scale of the first two women's football World Cup, the penalty for foul has increased, and the number of fouls with obvious effect has also shown a downward trend, which is why the proportion of pulling fouls is gradually decreasing.

4.5. Analysis of Experimental Environment and Parameters. In order to ensure the fairness of the test results, a foul action capture test room is set up, and three cameras are installed to obtain the action diagram. Parameter settings for machine vision system OV7670 model camera is shown in Table 2.

4.6. Accuracy of Feature Extraction of Fouls by Different Methods. The recognition parameters of foul behavior indirectly affect the accuracy of feature extraction of foul behavior. The larger the recognition parameters of foul action, the higher the accuracy of feature extraction. The

TABLE 2: OV7670 model camera parameters.

	Parameter	Numerical value
Resolution ratio	Input clock range/MHz	6–48
	Color filter array	RGB leaf pattern
		3856H × 2764 V
Maximum data Transmission speed	10 million pixels	3664H × 2748 V
	4:3: static mode	3840H × 2160 V
	16:9: video mode	
Source	Serial/Gbps	2.8
	Parallel/mp/s	80
	Data resolution/bit	12
	Consumption/m W	638
	SLVSI/O/V	0.4–0.8
	Analog voltage/V	2.4–3.1
	Digital voltage/V	1.7–1.9
	I/O digital voltage/V	1.8 or 2.8

TABLE 3: Comparison of foul action recognition parameters.

Number of tests	Based on Halcon Feature extraction Method	Based on FVRTS Features of the platform Extraction method	Based on machine vision Feature extraction Method of sense
20	5.12	5.12	10.23
40	5.02	6.45	9.45
60	5.00	6.00	9.84
80	4.03	6.21	9.91
100	4.10	6.33	10.03
120	4.20	6.49	10.00
140	4.44	6.45	9.02
160	4.79	6.66	9.15
180	3.98	6.94	9.45
200	4.91	5.48	9.60

identification parameters of foul behavior are obtained through experiments. The experimental results are shown in Table 3.

The data in Table 3 show that the range of identification parameters of foul behavior is 9.02–10.23, and that of traditional representative methods is 3.98–5.12 and 5.12–6.94, respectively. In contrast, the identification parameters of the proposed foul behavior are much higher than the traditional recognition method. This is because the method extracts the features of the foul image, establishes the potential function of the foul action sequence, and analyzes it in more detail. Thus, the accuracy of the method for the foul action recognition is improved.

5. Conclusion

In this paper, a method based on machine vision to extract the foul behavior characteristics of football players is proposed. By obtaining images and analyzing image features, the characteristics of foul behavior of football players are extracted. The simulation results show that the method can effectively identify the foul behavior of football players. The traditional football player's foul action feature extraction method is to describe the foul behavior as a series of symbols, decompose each symbol, and identify the foul action feature. However, the method has the problem of low feature

extraction accuracy in high-level football games. In order to solve the above problems, a method based on machine vision is proposed to extract the foul action characteristics of football players. Machine vision is a branch of the development of artificial intelligence. The target is converted into an image signal mainly through machine vision products and transmitted to the special image processing system.

Data Availability

The data underlying the results presented in the study are available within the manuscript.

Conflicts of Interest

The authors declare that there are no potential conflicts of interest in this paper.

Acknowledgments

This work was supported by Exploration and practice of the teaching mode of “substituting competition for practice and combining competition with practice” in college football under the background of Applied Talent Training (No. j2021735), teaching reform and innovation project of colleges and universities in Shanxi Province in 2021 (general project).

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