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ORIGINAL

Soccer Motion Track Recognition Based on Machine Vision and Image Processing

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Abstract

Sports programs are widely popular in today's society because of their unique charm. As one of the most popular sports videos, the analysis and research of soccer videos are receiving more and more attention from researchers. Due to the diversity of conditions in soccer games such as venue and color of clothing, there is no universal tracker that can perfectly adapt to all scenarios. Machine vision is the main means of acquiring information and understanding the world using computers instead of human eyes and brain. In the case of video images, by acquiring information under time series and fully exploiting its internal features after certain image processing, it can be used not only to effectively identify target objects, but also to locate moving targets, predict possible future motion trajectories of targets, etc. In this paper, we propose the recognition of soccer ball motion trajectory based on machine vision and image processing. Based on the in-depth study of feature extraction method of soccer ball, soccer ball target recognition based on target shape analysis, etc., we propose a practical and effective analysis for Vi Be algorithm and edge detection of image under machine vision of ball in soccer video. Therefore, the algorithm studied in this paper can better accomplish the task of multi-target tracking in soccer game scenes and can adapt to different scenes with strong robustness to changes in conditions such as field and clothing color, which is a successful application of machine vision in soccer trajectory recognition processing.

Keywords. Football track recognition, Machine vision, image processing

1. INTRODUCTION

In a bid to acquire external information, human beings mainly through the human body's various sense organs to achieve, such as vision, hearing, smell and taste, etc., and some studies show that 50% to 85% of them are obtained by the human eye, that is, vision (Hussien, Al-Jubouri, & Al Gburi, 2021). Due to the rapid development of computer-related technologies and the rapid spread of the Internet, people are increasingly receiving various information in the form of multimedia data, which requires the storage and analysis of various multimedia data (Hu & Hu, 2021). Therefore, vision is an important source for human to obtain information, and visual system has been an important direction of research (Han, 2021). Among multimedia information and data, visual information is mainly represented as images and video data, etc. Traditional soccer track recognition ignores the original color information of the image when recognizing the motion track of soccer arc ball, so the recognition results often have problems such as large error and slow recognition speed.

Among many sports competitions, soccer matches have the largest number of spectators and receive the most attention (Jiang & Tsai, 2021). Therefore, in motion trajectory recognition, to analyze the motion of a soccer ball, it is necessary to know the position of the soccer ball at each moment of motion (Wong et al., 2017). Trajectory recognition is a popular research direction in the field of machine vision, with many applications in defense, industrial, and civil scenarios, where one of the key algorithms is how to extract the features of an image (Tian, 2021). The central task of machine vision is the understanding of images, which contains the understanding of a single image, the understanding of multiple images, and the understanding of video images (Peng, Zheng, Li, Wang, & Zhong, 2020). In industry, there is now a gradual emergence of visual intelligent monitoring systems for product production, using cameras to achieve quality inspection of products In national defense, one of the key technologies for precision-guided weapons is the recognition of moving targets against complex backgrounds in the infrared (Moudjed & Rossi, 2019). A video scene is usually composed of a background and a target (Sun, Jiang, & Cheng, 2017). Among them, the target is an important part of the video data and contains important information (Wang, Ghosh, & Guo, 2001). Therefore, fast and effective detection of moving targets in the video and tracking of the target of interest are the basis for subsequent trajectory recognition analysis and processing (Kimachi, Hong, Shimonagata, & Asai, 2018).

At present, several applications have been derived from the analysis techniques of soccer sports trajectory recognition (Shen & Kang, 2007). For example, player motion tracking, 3D scene reconstruction, player hotspot activity map, VR video assistant referee, etc (Afraites, Atlas, Karami, & Meskine, 2016). The detection and tracking of ball targets in motion trajectory recognition is the basis for realizing these applications. The meaning of target recognition is to use a computer to process the image and obtain information about the target from the image, such as the type of target, location, etc. In the current game, arcing goals are generally used to improve the hit rate, so the arcing direct free kicks will be studied to analyze the better kicking points. The use of mature image target detection technology can provide stable and accurate detection results in addition to the analysis and classification of the problems found during the detection process.

The innovative points of this paper are as follows:

（1）This paper uses the soccer ball speed information obtained by Vi Be algorithm under machine vision to track the expected soccer ball trajectory, and combines it with arbitrary soccer ball recognition algorithm to improve the real-time performance of the recognition algorithm and solve the recognition problem when the soccer ball is obscured.

（2）The article considers that a video scene is composed of background and target, where the target is an important part of the video sequence and contains important information. Therefore, the fast and effective segmentation of objects in the motion trajectory and the tracking of the target of interest are the basis of the subsequent trajectory recognition analysis.

（3）In this paper, we use image processing and tracking filtering to achieve field segmentation, ball target detection, ball target recognition and tracking of soccer videos, so as to extract key information and events in soccer videos and help viewers better watch and understand the content of soccer videos of interest.

2. Related work

2.1 Football track recognition

In recent years, with the development of computer technology and the improvement of broadcasting technology, sports events are more often presented to the public in the form of video. The analysis of the video of soccer, rugby, tennis, billiards and other sports programs, especially for the most important of the above ball game video is the identification and tracking of ball targets. The study of soccer motion track recognition and tracking algorithms can help people to extract key information and events in the video quickly and effectively, help players and coaches to learn lessons to develop tactical strategies, provide better video services to viewers, etc.

Asai et al. extracted player activity areas based on thresholds for features such as area, aspect ratio, and color distribution, and used grayscale information with Hoff values to eliminate pitch areas (Asai, Nakanishi, Akiyama, & Hong, 2020). Mohan et al. performed matching between curve models with parameters and image data by using local statistical properties of images, and then searched for arbitrary contours between the target soccer ball and the background image (Mohan & Poobal, 2018). Alkali et al. used new parameters to improve the field extraction algorithm with the improvement of obtaining the color mean in RGB color space as the peak of the method in the literature and calculating the standard deviation from the new peak as the new threshold, which was experimentally shown to be satisfactory in terms of computational effort and extraction (Alkali, Saatchi, Elphick, & Burke, 2017). Mastriani proposed to use the edge extracted image information as input to the Adaboost learning algorithm and constructs a multilayer classifier and regression tree to achieve fast arbitrary soccer ball detection, which is able to detect different soccer balls in different environments but also has a high false detection rate when other circular objects are present in the environment (Mastriani, 2017). Gomez et al. proposed a set of color spaces containing multiple colors as a way to improve the algorithm to improve the generality of such detection methods. Although color features are robust to scaling and rotation, they are also subject to interference from lighting, shadows, and background colors (Gonzalez et al., 2017).

Among many sports games, soccer games have the largest number of spectators and receive the most attention. Therefore, it is of high practical value and relevance to detect, extract, localize and track the motion targets in soccer track recognition.

2.2 Machine vision and image processing

With the development of society, digital images are playing an increasingly important role in human society, and image processing theory and technology are receiving more and more attention from all walks of life. At the same time, machine vision is the use of computers to achieve human visual functions - the perception, recognition and understanding of the objective world three-dimensional scene, machine vision is a fairly new and rapidly developing research field, machine vision technology is widely used in various aspects. Therefore, both machine vision and image processing have a broad development prospect and high practical value.

Yagi et al. calculated the contour center based on the nearest contour point, constructed distance and angle geometric features based on the center, and expressed the features through a two-dimensional histogram, which was able to obtain the smoothness and symmetry information of the target (Yagi, 2017). A Y Z et al. divided the process of inferring a three-dimensional target from a two-dimensional image into three stages The first stage is the processing process using perceptual organization The second stage uses probability in the model matching process queuing method to reduce the search space the third stage finds spatial correspondence by solving for unknown observation points and model parameters (Zhong, Ma, soon Ong, Zhu, & Zhang, 2018). Kobayashi represents each contour point by finding the tightness of the approximate polygon, matches the tightness string by edit distance, and classifies the input shape according to the minimum edit distance(Kobayashi, 2017).

Beernaerts et al. proposed a theoretical framework for active vision, which controls the camera motion and coordinates the required processing tasks with external signals through a mechanism that actively controls the camera parameters in accordance with the available analysis outcomes and the present demands of vision (Beernaerts, De Baets, Lenoir, & Van de Weghe, 2020). Hao et al. extract feature triangles on multiple scales, construct triangle area and interior angle matrices to express the contours, and use the RM method to distance matrix The similarity between contours is measured by the matching distance (Zhang et al., 2017).

With the rapid development of microelectronics technology, real-time image processing has an increasingly wide range of applications in multimedia, image communication and other fields. In addition to the above mentioned machine vision and image processing methods, machine vision and image processing have been increasingly improved and updated in recent years with the vigorous development of research directions such as machine vision, which continuously improves its recognition efficiency and accuracy.

3. The idea of soccer track recognition based on machine vision and image processing

3.1 Feature extraction methods for soccer

In order to effectively distinguish a soccer ball from other targets on the field, appropriate features need to be selected to describe the soccer ball target (Javorova & Ivanov, 2018). Because the image is often disturbed and influenced by various noise sources during the generation process which deteriorates the image quality. In order to suppress the noise and improve the image quality, preprocessing such as filtering and smoothing must be performed on the image.

With the application and development of robotics, the application of robots is becoming more and more widespread, including assembly work in automated factories, harsh environment operations, deep sea operations and even space operations require the participation of robots. These charge signals are then converted into digital images using existing image acquisition cards and sent to the computer and its peripherals for the next step of analysis and processing. Identification of the velocity and displacement results of the soccer movement using polynomials.

$$\mathrm{S} = S(t) + \frac{b_1}{3}t^2 + \frac{b_2}{2}t^2 + b_3 t \tag{1}$$

S --The movement displacement of soccer curve ball recognized by the system

b_1, b_2, b_3 --The offset component of gravity acceleration in each axis direction of spatial coordinates in the process of soccer curveball movement.

tThe time from leaving the ground to the first contact of the curveball.

The movement of the soccer ball, the player, and the change of the camera viewpoint lead to changes in the position of the player area and the soccer ball area in the image (Malqui, Romero, Garcia, Alemdar, & Comba, 2019). In order to enable effective tracking of the soccer ball target, the tracking framework of the soccer ball is shown in Figure 1.

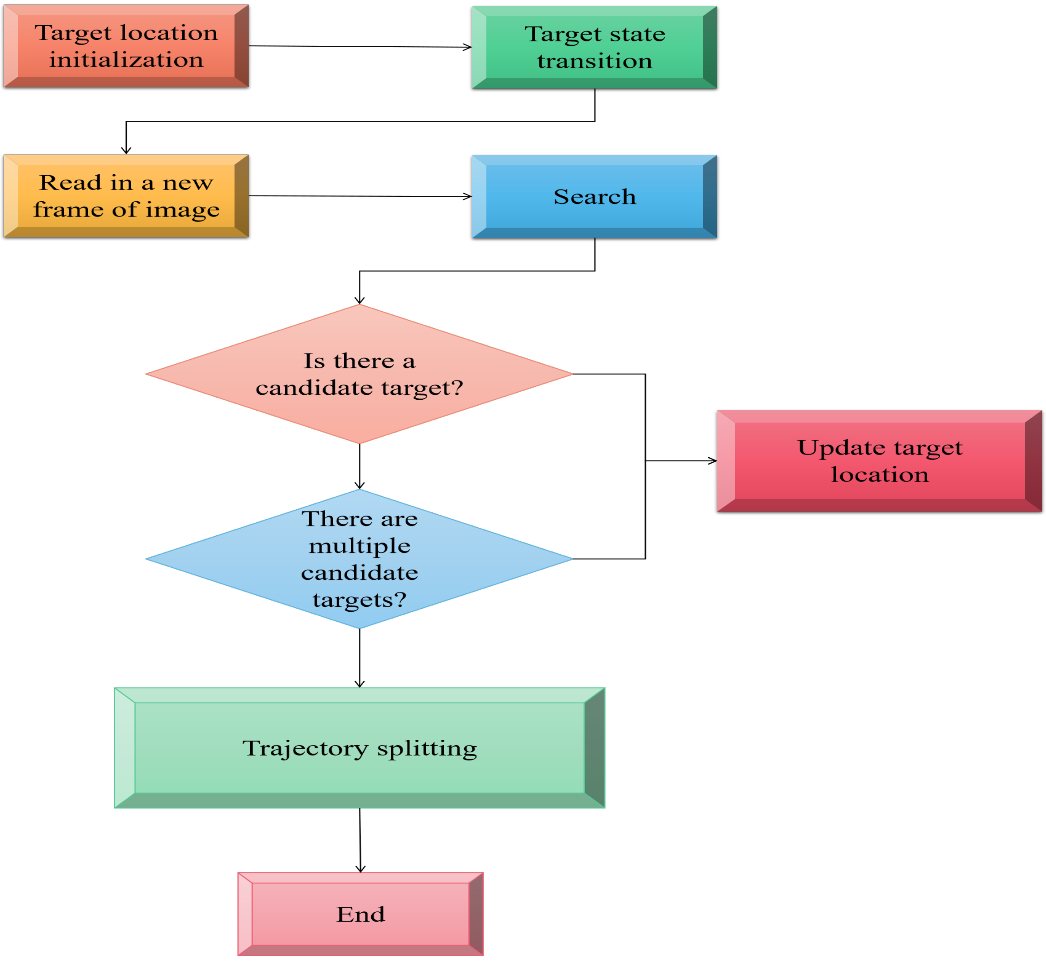

Figure 1. Block diagram of football target tracking

First of all, color feature extraction commonly used color models are color model, color model, etc. The RGB three-channel data is changed into a single-channel data image, and the image is changed from color to gray. The first task of tracking is to estimate the motion trajectory of the target and calculate the predicted position of the target at the next moment. Before designing the algorithm, a large number of soccer ball images need to be collected to build the sample set. A ball of mass m is kicked with initial velocity v_0 in the oxy surface and rotated around the axis passing through the center of the ball with w_0 as the initial rotational angular velocity to derive the basic model of the ball motion law:

$$\mathrm{x} = \frac{\mathrm{mv}_0}{\mathrm{Gw}_0}\sin\frac{G\mathrm{w}_0}{m}t \tag{2}$$

$$\mathrm{y} = \frac{\mathrm{mv}_0}{\mathrm{Gw}_0}(1-\cos\frac{\mathrm{Gw}_0}{m}t) \tag{3}$$

The edge detection operator is a linear operator, which can choose an optimal compromise between noise immunity and precise localization, which corresponds to Gaussian function smoothing and gradient computation of the image (Tong, 2020). The sample set is divided into two parts, a training set used to train the classifier and a test set used to test the performance of the classifier, where both the training and test sets each contain target and non-target images and are labeled as positive and negative sets, respectively. A finite difference of first-order partial derivatives is used to calculate the amplitude and direction of the gradient. The target segmentation extraction in the single frame soccer track recognition image, for the time being, does not consider the temporal correlation of the video sequence. The whole process of segmentation extraction can be represented in Figure 2 below.

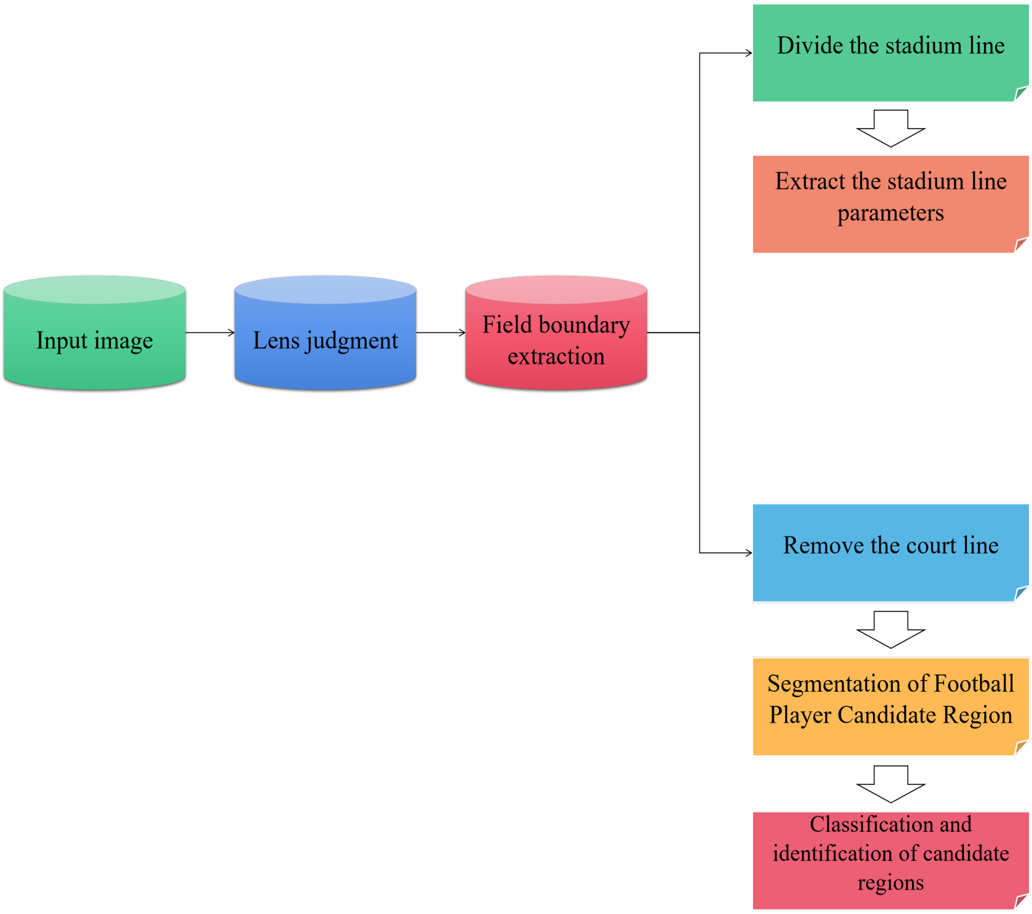

Figure 2. image processing flow chart of single frame football trajectory recognition

Next is the HOG feature extraction, which uses the distribution of gradient intensity and gradient direction in the local area to effectively characterize the shape and appearance of the target. The first-order difference operator will form large gradient values over a wide range, so it is not suitable for precise location, while the edges can be precisely located using the over-zero point of the second-order difference operator, but it is easy to obtain double edges. When multiple images are acquired with one camera at different positions and orientations for correction, where the rotation matrix and translation vector T are different for each image, but other parameters remain the same. Therefore, according to this characteristic, the parameters to be corrected can be divided into internal and external parameters, internal parameters do not change with the location and rotation of the laser, while the external parameters change with it. To achieve high measurement precision, a nonlinear model must be used to calibrate the camera system, describing the nonlinear aberrations of the image points can be used in the following equation:

$$\mathrm{x_u} = x_d + \xi_x, y_u = y_d + \xi_y \quad (4)$$

Finally, the system state transfer model is used to portray the motion characteristics of the target between two frames during the motion track target tracking. The more accurate the state transfer model is, the more accurately it can estimate the state of the target at the next moment. The overall contour is divided into contour segments, and the feature parameters are extracted as matching strings for the contour segments, and the dynamic programming algorithm is used to perform preliminary matching for each contour segment, which is a coarse matching process. Considering the differences in visual effects brought by different ratios of R, G and B, the ratios of the three components in the total components are divided according to the actual requirements, and the grayscale processing is realized by weighted summation. The bilateral filtering kernel is constructed by multiplying the Gaussian kernel function of the null domain proximity (spatial Gaussian kernel) with the Gaussian kernel function of the value domain similarity (luminance Gaussian kernel) by :

$$g(x) = \frac{1}{\mathrm{C}_{d,\gamma}} \sum_{x,y\in\Omega} w_d(x,y) w_r(x,y) f(x) \quad (5)$$

$f(x)$ ——Original image

$g(x)$ ——Output image

$w_d(x,y)$ ——Spatial information weight function

$w_r(x,y)$ ——Gray similarity weight function.

The multi-scale features extracted from the same target in two adjacent frames have some similarity, and there are some differences between different targets. So in this paper, we choose this multi-scale feature as the detection feature vector of the target and use the cosine similarity to measure the similarity between two feature vectors.

3.2 Soccer target recognition based on target shape analysis

The main idea of target shape analysis is to extract the feature information of the target region from the image and store it in a specific data structure for subsequent operations such as comparison, recognition, classification and retrieval (Weng & Guan, 2019). Although the detection features can calculate the similarity between targets to some extent, the detector is designed to classify the targets since the purpose of the detector is to classify them. So the more generic the detector is the more similar the extracted features are for similar targets, which leads to insufficient differentiation between detection features for similar targets,so it is necessary to use soccer target recognition based on target shape analysis. By calculating the center-of-mass position of each color grouping, the location information of the pixels is incorporated to make the tracking more accurate and rapid. To calculate the center of mass of each color unit i :

$$K_i^n = \frac{\sum_{i=1}^{n_h} \delta[b(X_i) - u] X_i}{\sum_{i=1}^{n_h} \delta[b(X_i) - u]} \tag{6}$$

n--Frame n image

X_i--Location of pixel points in the target area

μ--Histogram color values

b（X_i）--Color value of the pixel point

And the algorithm is adjusted and optimized accordingly by combining the imaging characteristics of omnidirectional vision and the specific problems of arbitrary soccer ball recognition to achieve a better soccer ball trajectory recognition based on target shape analysis. As a real-time target detection system based on machine vision technology, Figure 3 is used to illustrate the architecture and working principle of soccer ball target recognition based on target shape analysis.

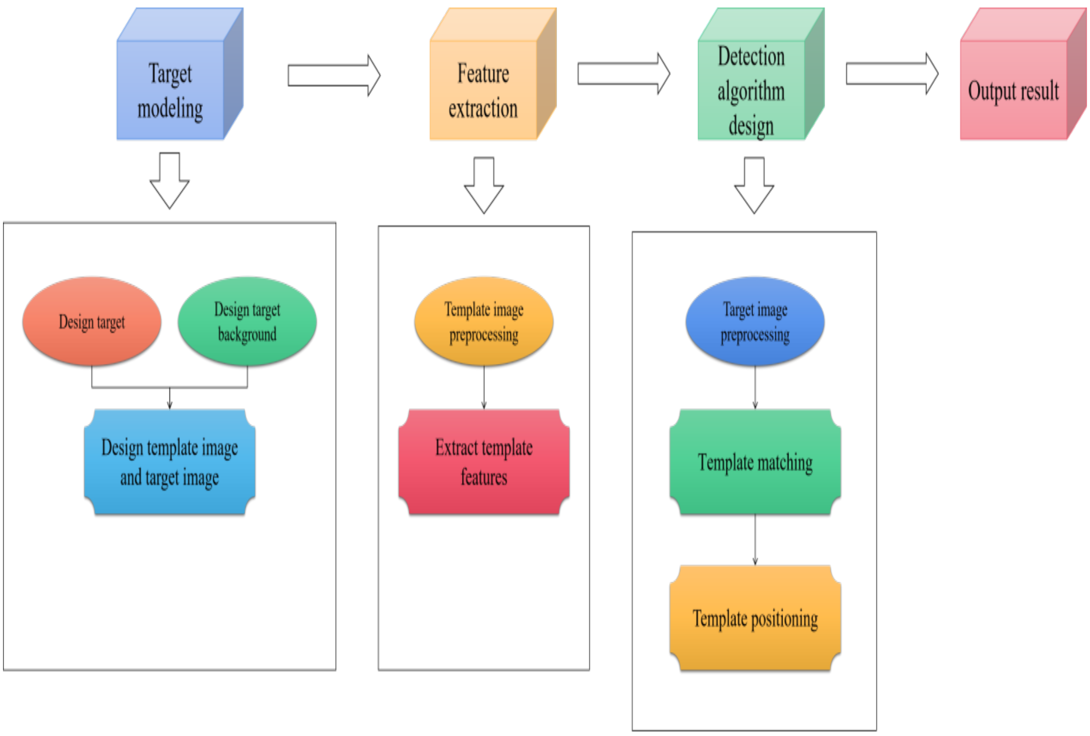

Figure 3. Football target recognition based on target shape analysis

First, for each connected region marked in the soccer field area, several shape descriptors can be used to describe the properties of the target region, such as area, perimeter and circularity of the region. The linear prediction technique only predicts the location of the target without predicting the error of the target location, so a fixed large search range needs to be determined to find the true location of the target.

The image segmented by thresholding obtained with Moravec operator works well to distinguish where the main regions of the target and background of the image are, so it is suitable for local thresholding. Moravec operator does not perform noise reduction on the image, so the response is sensitive to noise, while Harris uses a Gaussian function as a window function to suppress noise. To analyze the imaging relationships of different points on an image：

$$\mathrm{x_n} = K\left[R_1 \middle| T_i\right] X_n \tag{7}$$

The motion trajectory data are input into the Kalman filter model, and the new state data acquired subsequently are sequentially input into the update equation to obtain the dynamic soccer arc ball motion trajectory data with noise removed.

The perimeter of the region is equal to the point-by-point accumulation of the distance between the two points as defined above. The sample set required for the target recognition system with better recognition effect is at least several hundred images, and if the images are too few it may cause instability of the recognition algorithm. Then update the estimated value according to the measured value, and calculate the noise variance and forward prediction, and return to the Kalman filter model again, and the cycle repeats until the soccer arc ball movement stops, and the input update value is 0 when the filtering is stopped, and the data obtained at this time are the motion track data with the noise removed.

$$g(x,y) = \begin{cases} 1, if\left(f(x,y) \geq T\right) \\ 0, if\left(f(x) < T\right) \end{cases} \tag{8}$$

T ——Effect of image segmentation

The grayscale values between neighboring pixels within the same target or background are similar, but the grayscale of pixels on different targets or backgrounds varies widely. Reflected in the histogram, it means that different targets or backgrounds correspond to different peaks. By using high-pass filtering, high-frequency signals such as edges can be enhanced to make blurred pictures clear.

At different scales, the scale space of a 2D image can be obtained mainly by convolving the image as well as the Gaussian kernel as follows：

$$\mathrm{G}(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{\frac{x+y}{2}} \tag{9}$$

Finally, in order to reduce the computation and improve the efficiency of target screening, based on the observation and statistics of the trajectory to be processed, it is found that the area occupied by the soccer target region in the soccer video should be larger than 10 pixels and smaller than 30 pixels. The number of grayscale of the image is divided into 2 parts by gray level, and the optimal threshold is found by calculating the maximum value of variance between classes, so that the difference of grayscale value between two parts is maximized:

$$\mathrm{p}_i = n_i / N (i = 0,1,2,...,L) \tag{10}$$

$$\sum_{i=0}^{\mathrm{L}} p_i = 1 \tag{11}$$

N ——Total number of image pixels

n_i ——Number of pixels with a gray level of i

p_i ——Probability of gray level being i

For the positive set, i.e., the "soccer ball" set, the sample set needs to include more soccer balls with different colors, patterns and textures because of the randomness of the arbitrary soccer ball identification handled in this paper. The arc direct arbitrary ball is rotating flight, not only by the effect of gravity and air resistance, but also by the speed difference pressure perpendicular to the direction of flight, resulting in the initial trajectory of the soccer curved degree is small, and gradually increase. Then the grayscale values of each pixel in the image are compared with this threshold, and the corresponding pixels are divided into two or more classes according to the comparison result, considering pixels belonging to the same part as the same object, thus achieving the segmentation purpose.

4. Application analysis of machine vision and image processing in soccer track recognition

4.1 Analysis of Vi Be algorithm under machine vision

Because all the edge shapes to be detected are known, and Vi Be algorithm can easily get the boundary curve and connect the discontinuous edge pixels under the condition of knowing the shape of the region in advance, and the algorithm is simple, fast and effective, so we choose Vi Be algorithm. For the tracker, the difficulty of the scene is that once the target is obscured, it is difficult to retrieve the target once the tracking error occurs, and the comparison of the AUC curves of KCF and OAB algorithms is shown in Figure 4 below.

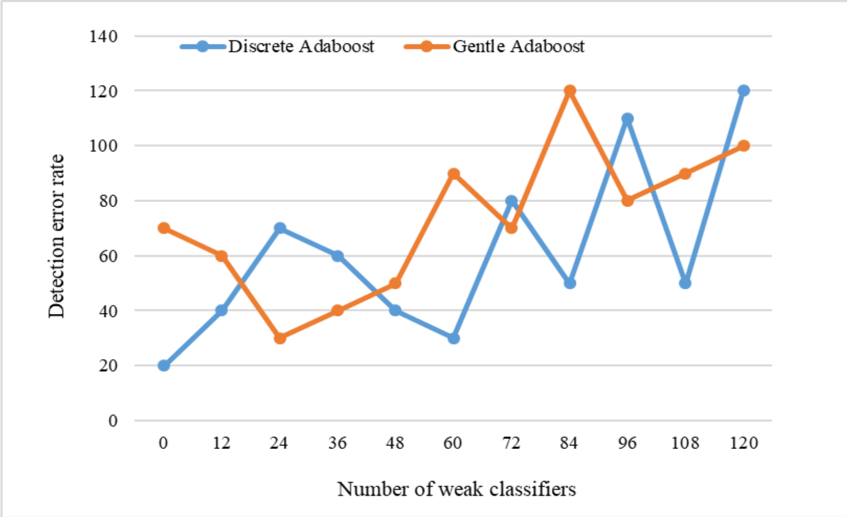

Figure 4. AUC curve of KCF and OAB

First, a sample set is created within each pixel field in the image, and a random sampling method is used to extract the pixel points in the sample set and compare them with the current pixel values to obtain foreground motion target information. A calibration plate is placed in the measurement field, and the calibration plate consists of a standard square square grid. Contrast grid lines are added to the screen image window with the same grid size as the square grid, and the central intersection line of the image is shown in green, while other lines are shown in yellow to facilitate calibration. The Sobel operator is used for edge detection, and then edge tracking is performed to obtain the complete closed edges as contours. As long as there is a known pixel within the boundary of a region, all other pixels in the region can be found from this pixel, and they are filled. That is, when the probability density peak is close and the gradient is small, it will move in smaller steps; when it is far from the probability density peak and the gradient is large, it will move in larger steps. As shown in Figure 5, the detection error rate of Gentle Adaboost is lower than that of traditional Adaboost, i.e. Discrete Adaboost, in the two-class problem.

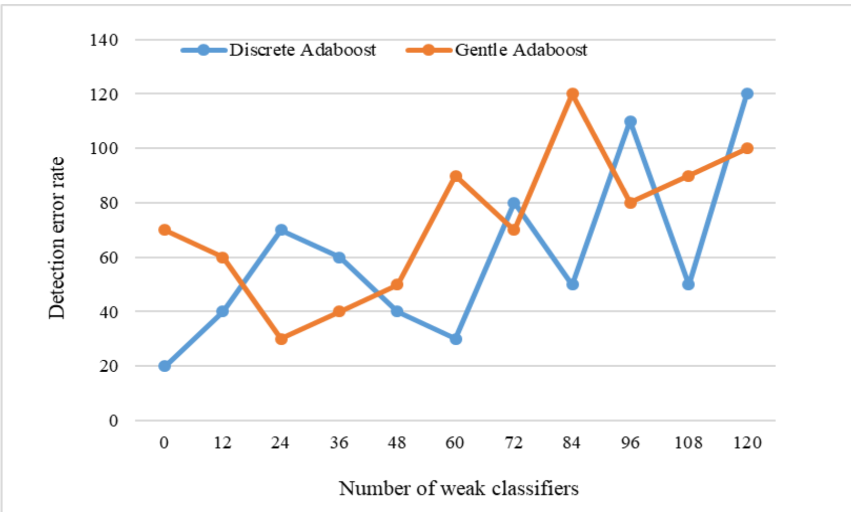

Figure 5. Performance comparison diagram of discrete AdaBoost algorithm and Gentle

Adaboost algorithm

Second, the background model is simultaneously updated using a stochastic policy approach, so the algorithm can be understood simply as a classification detection problem for pixel points. Through the imaging computation process of the generic camera model from the objective scene to the digital image, the coordinate point corresponding to it in the calibration plate image ingested by the camera is calculated. If this coordinate point is outside the image range, it is blacked out, otherwise its data value is read out and assigned to the corresponding pixel point. Thus the target segmentation step directly uses the global threshold segmentation method to binarize the image and achieve the segmentation of the target object from the background. The gray value used for the actual comparison is the sum of the gray value of the input image pixel and the output value of the error diffusion filter first, and then the actual compared gray value enters the threshold comparison after passing the threshold quantizer, and the compared value is 1. By the feature that the pixel point has similar spatial distribution with its surrounding domain pixel points, the background model sample value is constructed by randomly selecting the neighboring domain point pixel values for all pixel points in the first frame image The background model sample values are constructed. When the number of features is 100 than 200, the increase of recognition accuracy of the system is small, so the number of features is 200, which is suitable for considering the performance of the algorithm and the real-time of the system, as shown in Figure 6 below.

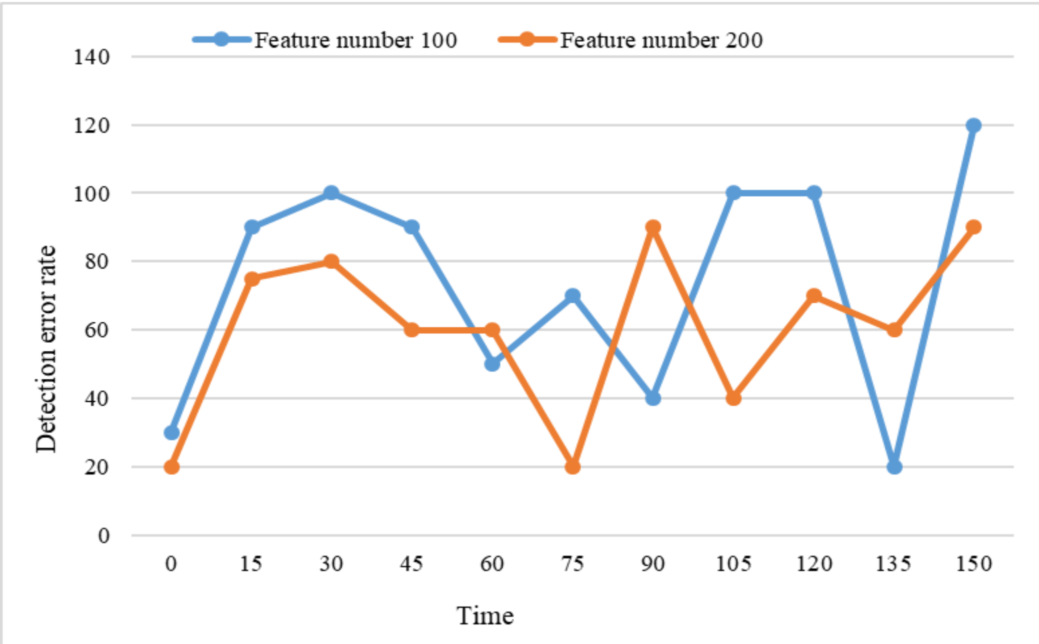

Figure 6. Schematic diagram of the relationship between the detection error rate of recognition algorithm and the number of features

Finally, for the case of abrupt background changes, the algorithm simply discards the current frame background model and rebuilds the background model sample set based on the changed frame image. Since the accuracy of the calibration directly affects the addressing error of the feeding device and adjusting a parameter affects other previously tuned parameters, patience is required for repeated adjustments, and the positions of the yellow and green lines are always unchanged when adjusting the image. The thresholds are compared with the actual grayscale values to obtain the error into the error diffusion filter, and the error is diffused through the error diffusion filter to the surrounding unprocessed pixels. This ensures that the peak of the local optimum can be found quickly. Since the target tracking application, the moving type of the target changes continuously, and it is originally a local optimization-seeking process, so there is no need to worry about falling into local extremes.

4.2 Edge detection analysis of images

The edge of an image is a reflection of the discontinuity in the local characteristics of the image (grayscale mutation, color mutation, etc.). It marks the end of one region and the beginning of another. The deformation transformation of an image transforms the coordinates of each point of the source image into the new coordinates of the corresponding point of the target image by the deformation operation. However, this leads to the problem that the coordinates of the target points are usually not integers, and the image scaling operation results in points in the target image that are not mapped to the source image. Therefore, edge detection analysis of the images is necessary. The selected dataset consists of 65 telephoto shot frame sequences from 120 soccer game videos, totaling 22550 frames, each motion trajectory consists of start frame, end frame and the target's enclosing frame position and size information in each of them. The specific motion trajectory scene information is shown in Table 1.

Table 1. Track Set Scene Distribution

Scene	1	2	3	4
Trajectory number	1-30	31-60	61-90	91=120
Count of tracks	20	15	15	15
Total frames	6744	4568	7692	3546

First, the discontinuities in the local characteristics of the image are detected, and then these discontinuous edge pixels are concatenated into a complete boundary. The area occupied by a soccer target in the upper part of the image is usually smaller than the area occupied by a soccer target in the lower part of the image. Therefore, the sample set needs to include a variety of situations such as strong, moderate and weak illumination. Then the grayscale histogram can be seen as a histogram consisting of two single peaks of the target and the background. If the mean values of these two single-peak grayscale distributions are far apart, the mean squared difference is small, and the number of distributions is not too different, then the mixed histogram is bimodal, and such images can be well segmented using the grayscale threshold method.

In order to verify the recognition efficiency of the soccer ball movement in three-dimensional space, the starting point position is noted as the origin during the experiment, and the recognition results of the traditional system and the system in this paper are compared with the soccer ball movement trajectory. The results are shown in Table 2 below.

Table 2. Comparison of experimental results

Football track	Track 1	Track 2	Track 3	Track 4	Average offset
System identification result offset in this paper	0.012	0.018	0.016	0.021	0.017
Traditional system identification result offset	0.056	0.067	0.082	0.079	0.071

As can be seen from Table 2, the average offset of recognition results of this paper's system is 0.017, while the average offset of recognition results of the traditional system is obviously 0.071 The offset of recognition results of the traditional system, the results of this paper's system are obviously smaller than the traditional system. That is, for the traditional system, the error of the intelligent recognition system of soccer arc ball motion trajectory proposed in this paper is relatively smaller. Secondly, the neighborhood of each pixel is checked and the rate of grayscale change is quantified, which usually includes the determination of direction as well. It outputs the gray value of a pixel equal to the gray value of the nearest input pixel to the position it is mapped to, and the nearest neighbor algorithm is simple and fast to implement. Apparent features are used to calculate the similarity between targets. When using ideal apparent features, the similarity between detections from the same target is larger, while the similarity between detections from different targets is smaller. The target search is performed within the target prediction range obtained from the target motion estimation, and if a target is detected within the prediction range and there is only one, then target matching is not required and the target can be considered as the target to be tracked. Median filtering is used in image smoothing because it is suitable for dealing with pepper noise and impulse noise, and it has less effect in boundary processing, and the edges of the smoothed image will not be blurred like other smoothing techniques.

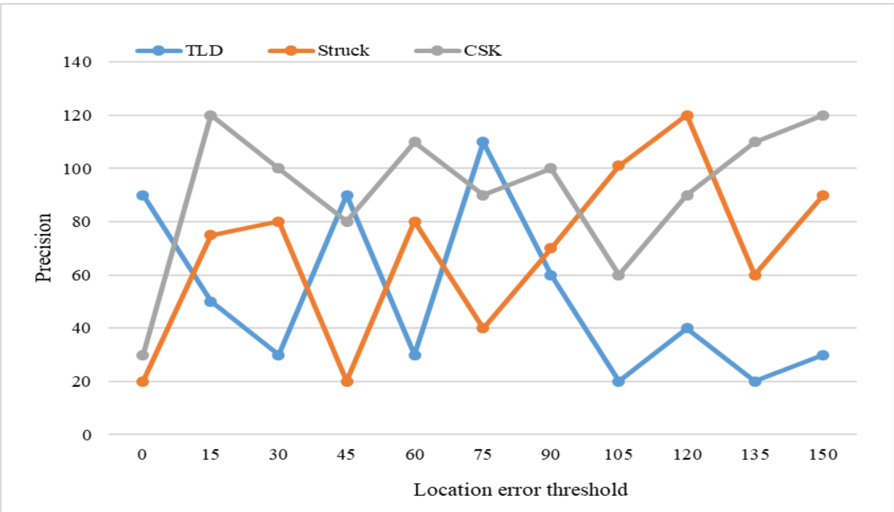

Figure 7. Comparison chart of ope accuracy

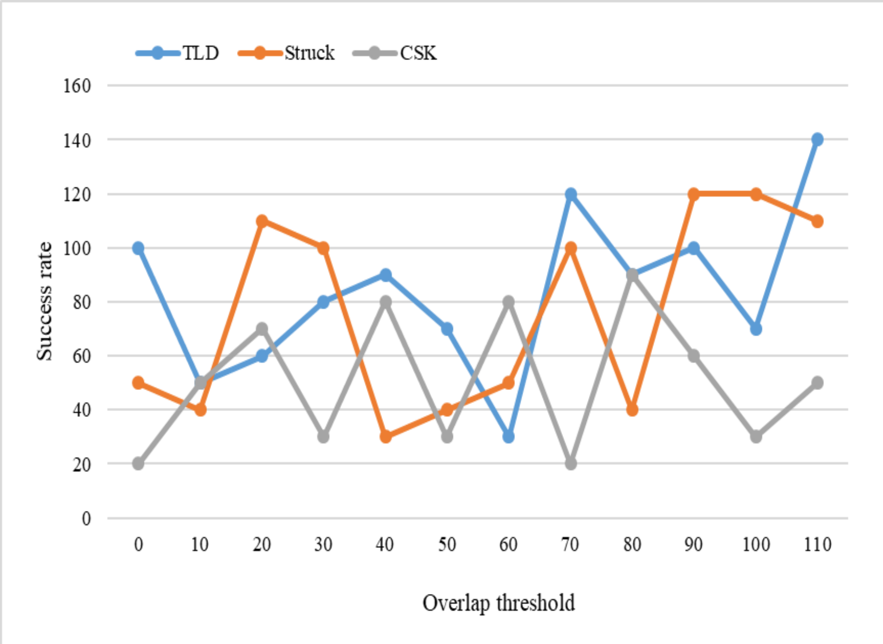

Figure 8. Comparison chart of OPE success rate

Finally, all edge templates are applied one by one to each pixel in the image to produce the edge template with the largest output value as a candidate template whose direction indicates the direction of the edge at that point, and if the edge templates in all directions are close to zero, then there is no edge at that pixel point. The dithered square matrix is expanded to the same size according to the columns and lines of the dithered picture, and then the pixel values of the pixel points in the image are compared in size with the corresponding position elements from the expanded dithered matrix, and if the pixel values are not smaller than the corresponding values in the dithered matrix, then the pixel points are set to 1, and vice versa. Edge tracking starts from the top left corner of the image, and when an edge point is encountered, sequential tracking starts until the following point returns to the starting point (for closed lines) or there is no new following point (for non-closed lines).

5. Conclusions

Sports video is an important class of media data and has a special charm that is enjoyed by a wide audience. Soccer tracking technology is of great significance for game commentary, tactical analysis, penalty aids and video special effects. The research of sports target tracking process faces many difficulties due to the variability of the shape of the sports target, the variability of the environment, and the increased demand for real-time performance. Machine learning can effectively retain the structural characteristics of the target and describe the details of the target in a targeted manner, which has better results in target tracking applications. Image processing can obtain the trajectory equation of image edges through image segmentation, contour extraction, edge detection, curve fitting and other processing methods, and then output to the lower computer through serial communication, while incorporating color feature extraction to improve the tracking accuracy and robustness of the tracking algorithm. In this paper, we propose a soccer ball trajectory recognition method based on machine vision and image processing, and make a systematic study on the theory and method of image segmentation and image matching and the application of campaign algorithm in image segmentation and image matching, and provide a detailed description of the related hardware and software while realizing the recognition of the trajectory, and prove the performance of the system through experiments.

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