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Research Article

Research on Sports Video Image Analysis Based on the Fuzzy Clustering Algorithm

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Aimed at the shortcomings of the current sports video image segmentation methods, such as rough image segmentation results and high spatial distortion rate, a sports video image segmentation method based on a fuzzy clustering algorithm is proposed. The second-order fuzzy attribute with normal distribution and gravity value is established by using the time-domain difference image, and the membership function of the fuzzy attribute is given; then, the time-domain difference image is fuzzy clustered, and the motion video image segmentation result is obtained by edge detection. Experimental results show that this method has high spatial accuracy, good noise iteration performance, and low spatial distortion rate and can accurately segment complex moving video images and obtain high-definition images. The application of this video image analysis method will help master the rules of sports technology and the characteristics of healthy people's sports skills through video image analysis and help improve physical education, national fitness level, and competitive sports level.

1. Introduction

Web systems are substantially different from more conventional software systems. They are developed in shorter time frames and with smaller budgets, meet a more generic set of requirements, and generally serve a less specific user group [1]. They are often developed very quickly from template solutions, using coarse-grained authoring tools, and by the efforts of a multidisciplinary team [2, 3]. With the rapid development of network and multimedia technology, many sports operations and national fitness materials are stored in various health guidance systems in the form of video and pictures. In order to better promote the public fitness, easy to learn and see, sports video also has editing, segmentation, and integration of a variety of needs. Video compression technology has gradually become a hot research topic [4, 5]. An intelligent scheduling algorithm for hierarchical data migration is a key issue in data management. The discovery of mass media content platforms and usage patterns of content objects is the basic timetable for data migration. We added QPop (the dimensionality reduction result of media content usage logs) as a content object for discovering usage patterns. On this basis, a clustering algorithm QPop is proposed to increase time segmentation, thereby improving mining performance.

Video compression technology reduces the video capacity by video coding, which facilitates the release of storage space and reduces the transfer time. The traditional video coding standards include mpeg 2H., 263, and .mpeg, which refer to moving picture group of experts, as the group of experts on dynamic images. Its computational redundancy is small, and the overall efficiency is higher than that of stable h.263 [6]. In addition, the video coding technology needs to segment the object image to ensure the integrity of the target object. However, the traditional video coding standard cannot search the content of the video. It has a certain degree of difficulty in image segmentation. Mpeg 4 is introduced in 2000 as the semantic search function of video content, which can divide the image background and foreground into different semantic objects. The coding efficiency is improved, but the noise cannot be eliminated quickly in the coding process [7].

The rest of this paper is organized as follows. Section 2 discusses research on motion change region detection, followed by research approach which is discussed in Section 3. Detection of the motion change region with multiple

constraints is discussed in Section 4. The experiment is discussed in Section 5. Section 6 concludes the paper with summary and future research directions.

2. Research on Motion Change Region Detection

Time-domain segmentation and frequency-domain segmentation are the first methods proposed for moving video image segmentation. It has been proven that both two methods cannot accurately depict the object posture and the image segmentation is not clear. Therefore, based on a fuzzy clustering algorithm, the research on sports video with strong motion and attitude changes will be helpful to better use and analyze sports video images. The fuzzy clustering algorithm comes from pattern clustering theory.

2.1. The Basic Method of Motion Change Region Detection. It is an algorithm that uses mathematical rules to describe the segmentation interval. The fuzzy clustering algorithm uses iterative operation to segment the pixel region of the target object and divide the image pixel into different subordination intervals to make the image segmentation decision [8]. When the target object has n pixel samples, the pixel samples form an uncluttered set, which is represented as $x = \{x1mx2, \text{and } XN\}$, and XK represents pixel samples. Let c denote the number of image segmentation types and λ denote the fuzzy clustering weighting factor [9]. The moving posture of target objects in sports video is relatively random, the trend of image change is blurred, and the segmentation area is not easy to determine. The proposed method of video image segmentation can divide the moving attitude area of the target object into the foreground and the background and extract the motion of the target object. The class algorithm extracts the image sequence in the sports video playback state and opens the edge detection process at the same time [10–12]. According to the image sequence, the object motion is predicted and compensated. The same background is set up on some images with small spacing.

2.2. Fuzzy Clustering Algorithm. The time-domain difference image is extracted by using the attributes of the adjacent image frames. The fuzzy attribute in the motion process of the object and the corresponding membership function are written. After the fuzzy clustering of the time-domain difference image, the edge contour of the object is cut through the edge detection process, the foreground region is obtained, and the foreground area is eliminated. The following two problems need to be discussed for the selection of fuzzy attributes in the fuzzy clustering algorithm: the first is which attributes of the target object can accurately describe the operational attitude and the second is that the ambiguity in the motion pose region and the useless pixel region is not the same and there must be obvious difference [13–15].

After discussion, the proposed sports video image segmentation method finds that when the object in the moving video image goes through motion prediction and compensation, the background region can be expressed as the background difference of the image with small spacing and the same background [16]. In this case, if the background of the original sports visual frequency image has normal distribution, then the segmented image should also have the normal distribution property, and the average pixel distribution is equal to 0 which is shown in Figure 1 [17].

The judgment matrix A meets the following requirements:

$$a_{ij} = \frac{a_{ik}}{a_{jk}}, \quad i, j, k = 1, 2, \cdots, n. \tag{1}$$

When the consistency of the judgment matrix does not meet the requirements, there are nonzero eigenvalues:

$$\lambda_{\max} + \sum_{\lambda \to \lambda_{\max}} = \sum_{i=1}^{n} a_{ij} = n. \tag{2}$$

In order to check these matrices to determine their consistency satisfaction, the average random consistency index RI value (1-9) order judgment matrix is introduced:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1}, \tag{3}$$

Level single sort: CR can be used to judge [18].

Level total ranking: for all factors from low to high level, calculate their relative importance to the highest level.

The upper-level A contains m factors $A1$, $A2$, and Am and the level total ranking weights $a1$, $a2$, $a3$, and am; the next level B contains n factors $B1$, $B2$, and Bn and the single-level ranking of factor A_i; the weights are $b1$, $b2$, $b3$, and bn; and the total ranking weight of the B level can be filled as shown in Figure 1.

Consistency check sequence level total ranking: consistency check sequence level total ranking results also need to be checked. The process of consistency checking progresses gradually from the lowest level to the highest level [19]. If the consistency index of the B-level elements for A_i single sorting is C_{lj} and the average random consistency index is R_{lj}, then the B-level total sorting random consistency ratio is

$$\mathrm{CR} = \frac{\sum_{i=1}^{m} a_i \mathrm{CI}_i}{\sum_{i=1}^{m} a_i \mathrm{RI}_i}. \tag{4}$$

If CR < 0.1, the total ranking result is satisfactory, indicating that the total ranking result of layer B meets the consistency requirements [20]. The relative importance weight of this layer is the total ranking weight result of this layer and the relative weight of the research object [21].

Figure 2 is a flowchart of the fuzzy clustering algorithm, which reflects the calculation process of the entire algorithm. The biggest task in AHP is to calculate the maximum eigenvalue and eigenvector of the judgment matrix.

$$w_i \frac{\bar{w}_i}{\sum_{i=1}^{n} \bar{w}_i} \bar{w}_i = \sqrt[n]{M_i}. \tag{5}$$

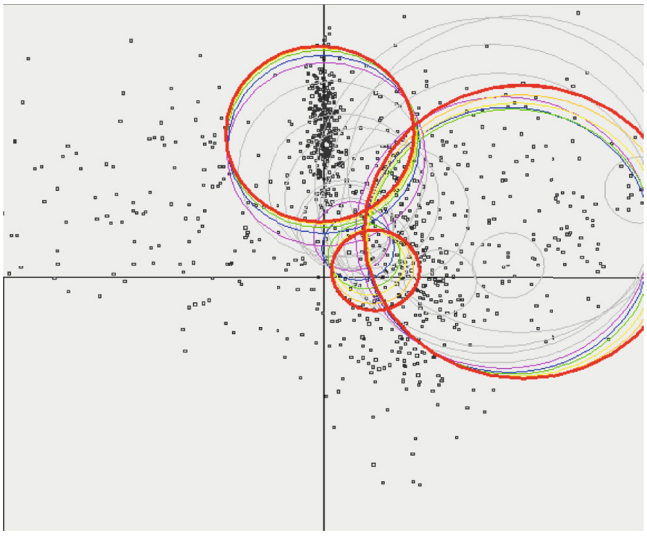

Figure 1: Fuzzy clustering algorithm.

The maximum characteristic value is

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(BW)_i}{nw_i}, \tag{6}$$

in which, λ is the i-th component of the product of the judgment matrix B and the eigenvector W.

Establish a regression equation [22]:

$$X_t = \sum_{i=1}^{k} \alpha_i X_{t-i} + \sum_{i=1}^{k} \beta_i Y_{t-i} + u_{1t}. \tag{7}$$

If the null hypothesis does not constitute a causal relationship, then the null hypothesis holds:

$$F = \frac{(\mathrm{SSE}_r - \mathrm{SSE}_u)/k}{\mathrm{SSE}_u/(T-2k)} \sim F_{(k,T-2k)}. \tag{8}$$

2.3. Interframe Difference Method. The pixel distribution of the segmentation image foreground cannot be determined directly and the foreground region cannot be extracted, so the gravy level measurement of the image is needed. The gravy level difference of different frame image pixels in the background is not different, but the gravy level difference of different frame image pixel points in the foreground must be larger than that of the background.

According to this personality quality, the gravy value can be regarded as an important attribute when selecting fuzzy attribute. On the other hand, the single fuzzy attribute has little gain on the segmentation effect and can proceed from the normal distribution of the background. The image segmentation process between the motion pose region and the useless pixel region is treated as a process of describing the nonnormal distribution pixels in the normal distribution pixels. In reference, a fourth-order matrix is used to extract the non-normal distributed pixels, and the time-domain difference image is considered as a pixel point, and a moving hollow rectangle is used to measure the time-domain matrix of the image.

There are many kinds of membership function of the fuzzy clustering algorithm, in which the "s function" can consider the big difference of fuzzy attributes between the foreground and background in sports video image and can provide two kinds of membership degree, which is very small and convenient for partition. Therefore, the s function is used in foreground image segmentation. The background image has a large noise and normal distribution, so it is necessary to select the membership function which can provide the time-domain variance.

3. Research Approach

In this paper, a complete and consistent moving video object is segmented from a video sequence towel. In this paper, a segmentation algorithm based on fuzzy clustering is used to obtain the pixels constituting the image boundary, and then, the object is extracted. The algorithm first uses the image information of the current frame and some previous frames to calculate its motion features in different subbands in the wavelet domain and constructs the motion feature vector set of the low-resolution image based on these motion features.

Then, the motion feature vector set of the low-resolution image is constructed. The mean value clustering algorithm separates the pixels, whose rifle has changed significantly in order to replace the frame difference image, and uses the traditional change detection method to obtain the object change detection model and then extracts the object. The average absolute difference between successive frames is used to determine the number of frames needed to calculate the motion characteristics of the current frame to ensure the accuracy of extracting video objects. Experimental results show that the proposed method is effective for the segmentation of video objects with various image sequences.

Object-based video segmentation plays an important role in the field of digital video processing and computer vision. The task of video object segmentation has been integrated into many applications, such as object-based video coding (mpeg.4111) and content-based video indexing and restoration (mpeg.7121). Therefore, the segmentation of video sequences into video objects has become a very important problem in digital video processing.

4. Detection of the Motion Change Region with Multiple Constraints

At present, there is a variety of moving object segmentation algorithms, and the change detection based on interframe difference is a popular segmentation method. Because of its simple implementation, this method is widely used in the development of a fully automatic video processing system based on an object.

4.1. System Theory Model. However, the method based on interframe difference change detection also has some shortcomings. These shortcomings include the error area caused by noise and the uncovered area caused by object motion. In order to solve this problem, we propose a new robust

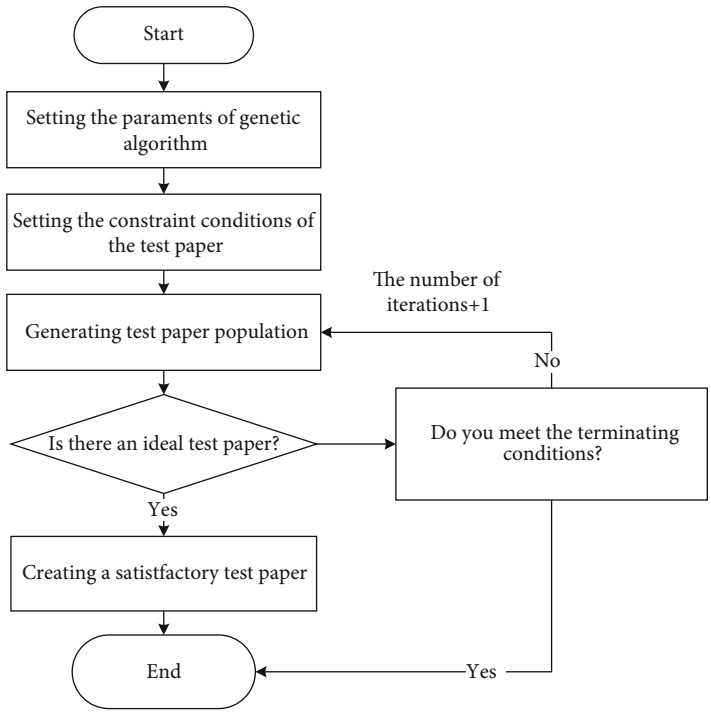

Figure 2: Flowchart of the fuzzy clustering algorithm.

semantic segmentation algorithm based on a frame difference image boundary graph. However, the algorithm will still be affected by background noise.

In addition, because the criterion of these methods is frame difference, the frame difference depends on the moving speed of the object. If the moving speed of the object changes greatly in the sequence, the segmentation quality is difficult to be consistent.

Therefore, interframe difference change detection is introduced into the wavelet domain to process, thus increasing the number of pixels constituting the boundary of the object. Although these methods improve the segmentation quality to some extent, the difference of segmentation quality caused by moving speed still exists. At the same time, in the segmentation process, the rifle needs to test the significance of each subband image in each frame to determine the domain value of the separation noise, thus increasing the computational complexity. Different video sequences, as well as different frames in the same sequence, have different noise levels, so it is difficult to determine the exact domain value, which leads to the inaccuracy of segmentation. Error analysis of sports video images is shown in Figure 3.

As shown in Figure 3, our proposed clustering algorithm has a good simulation effect. According to the speed of the object, the information of different frames is used to determine the motion information of the image in the wavelet domain rifle, which constitutes the motion characteristics of each frame of the image, and the pixels of the moving image are changed by separating the image.

4.2. Differential Image Block. Finally, changing pixels are used instead of interframe difference, and the accurate video moving object is segmented by the traditional method of frame difference change detection combined with the spatial boundary information of the image. The principle of moving object segmentation based on fuzzy clustering is like that of the traditional interframe difference detection method. The difference is that the traditional wavelet domain change detection method is not directly used to detect the difference between frames. It is based on the change of the image in the wavelet domain to obtain its motion characteristics.

For this purpose, an operational feature vector set is constructed by using the mean square error of each subband in the wavelet domain between the current frame and some previous frames, and the object is segmented by the fuzzy clustering method. The algorithm of the article is based on this situation for the case where the background is moving, and many researchers have proposed the use of global motion estimation and compensation to deal with the background changes caused by camera motion. Therefore, the input sequence is assumed to be a compensated sequence, and its background region is stationary. The algorithm is divided into four main parts: wavelet transform and feature calculation, fuzzy clustering and change detection, detection of moving object boundary, and object extraction.

4.3. Relative Noise Characteristic Parameter Estimation. The motion change of the towel video object will be reflected on all its wavelet subbands. The motion characteristics of each pixel in the low-resolution image may be a 4-dimensional vector for each pixel in the low-resolution image.

Because the image of the frame is used in motion feature calculation, its purpose is to obtain more information of object motion change, but when the number of frames is larger, it will produce a large uncovered area, so the number of frames must be controlled. When the object's motion

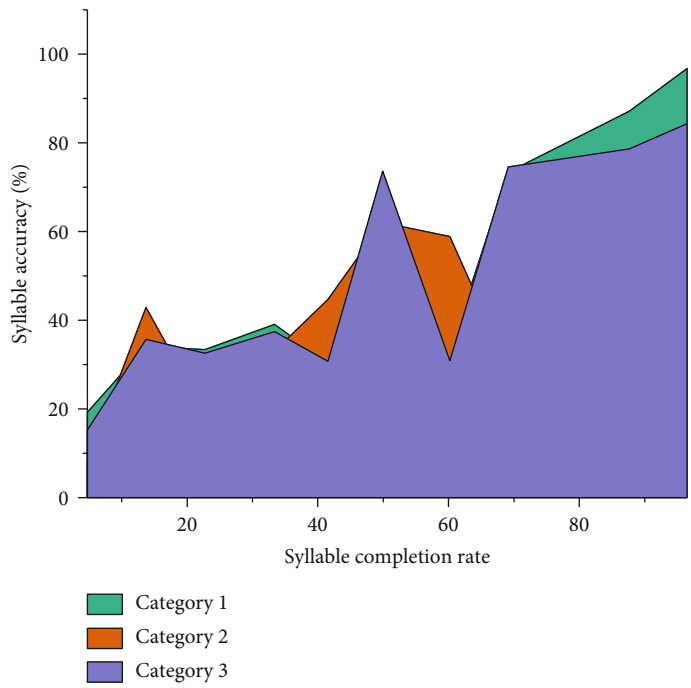

Figure 3: Error analysis of sports video images.

changes greatly, there is enough change information to extract the object, so the number of frames needed should be less; on the contrary, when the object's motion changes slowly, there are fewer pixels to change, in order to obtain enough pixels to form the boundary of the object. More frame information is needed to ensure the accuracy of object segmentation. The value of the object is determined by the change of the object motion, which can be evaluated by the mean absolute difference between successive frames.

In this paper, an algorithm of motion edge segmentation based on fuzzy clustering is proposed. By analyzing the motion characteristics of each subband image in the wavelet domain, the algorithm obtains the feature vector set of its operation and uses fuzzy *c*. The mean clustering algorithm is used to obtain the pixels in the low-resolution image. Finally, the boundary of the moving object is obtained by using the traditional change detection method instead of the difference between frames, and then, the object is extracted. The experimental results show that the proposed method can obtain more accurate shape information of video objects and extract moving objects of different video sequences accurately. Video object generation has important applications in many aspects. It is not only the basis of content-based video coding but also an important link in the video image tracking and recognition system. Because the video object (moving object) exists in the moving change region, one of the important methods of video object generation is to detect the motion change region first and then combine other features to generate the video object in the motion change region.

5. Experiment

The accurate detection of the motion change region is the key of this kind of method, so the research of motion change region detection is of great significance. Analysis of sports video images in different environments is shown in Figure 4.

As shown in Figure 4, our two proposed detection methods of the motion change area have a good prediction effect. The first method is based on noise feature parameter estimation and energy analysis. This method uses a block-based frame difference processing method, and uses the dual constraints of Gaussian distribution and relative noise characteristics of energy attributes to detect motion change areas. Compared with the traditional pixel-based interframe difference method, the computation is less. The threshold of relative noise estimated according to the characteristic parameters of relative noise is generated by self-adaptation in the process of detection. At the same time, the accuracy is improved by the correction of energy analysis. Performance analysis of the fuzzy clustering algorithm in different environments is shown in Figure 5.

As shown in Figure 5, our proposed method is more superior in performance; firstly, this paper discusses the general theory of time-difference video segmentation. Based on the video segmentation model established by Keri, a method of automatic detection of the video motion change region is proposed from the point of view of fuzzy entropy clustering. Based on the established fuzzy classification criterion, the motion change region and the relative noise-sound region are divided in the differential image, and the motion change region is obtained. The visual analysis of human motion mainly deals with the sequence of human motion images. It usually involves the detection of the region of motion change, the movement tracking resistance of the human body, and the understanding and description of the target behaviour in the monitoring scene. Among them, behaviour understanding and description belong to advanced processing, which has been paid more and more attention in

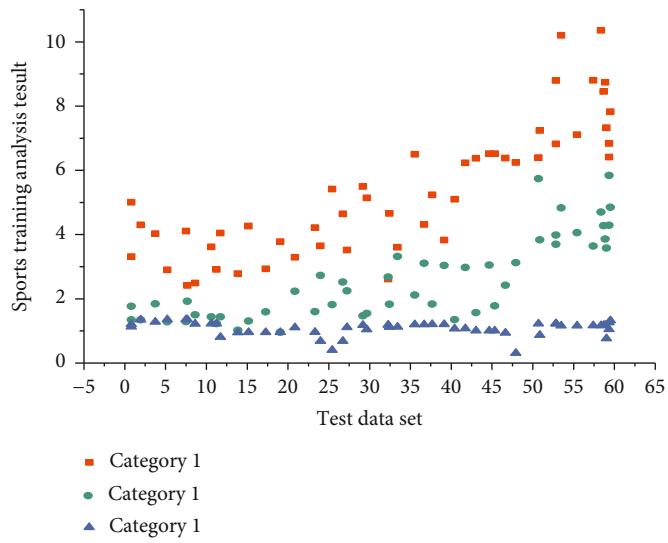

Figure 4: Analysis of sports video images in different environments.

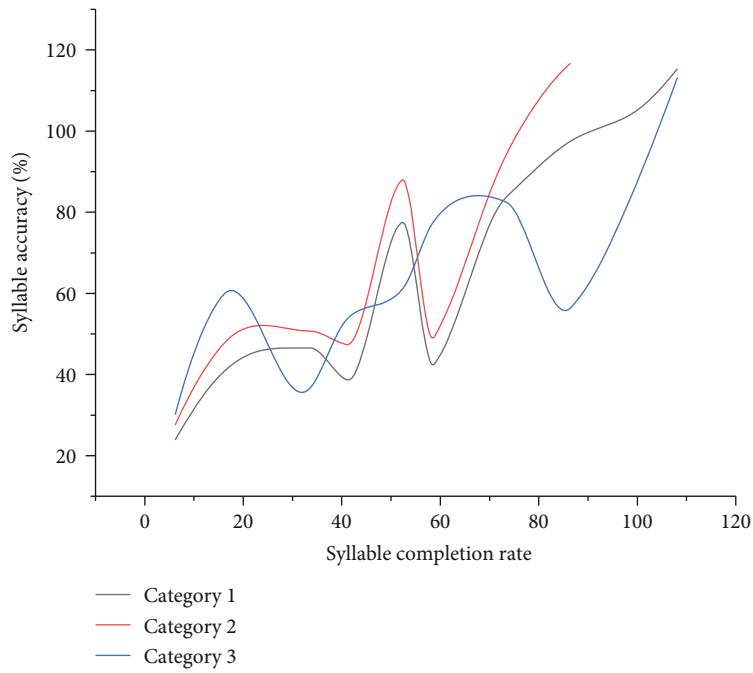

Figure 5: Performance analysis of the fuzzy clustering algorithm in different environments.

recent years. Performance analysis of sports video images under different standards is shown in Figure 6.

As shown in Figure 6, the simulation results of the fuzzy clustering algorithm proposed in this paper are more evenly distributed and have higher accuracy. It refers to the analysis and recognition of moving patterns of targets and the description of them by natural language. In the area of motion change detection, human motion tracking belongs to the low-level processing part of vision, which is the basis of various subsequent advanced processing such as behavioural understanding, and is also the two more studied problems in visual monitoring. Of course, there may also be intersections between them (for example, sometimes motion detection is used during tracking). Background subtraction is one of the most used methods in motion detection at present. It is a technique to detect the motion region by using the difference between the current image and the background image.

It is generally able to provide the most complete feature data, but it is particularly sensitive to changes in dynamic scenes, such as illumination and the interference of unrelated events. The simplest background model is the time-averaged image. Most researchers are currently working on developing different background models in order to reduce the impact of dynamic scene changes on operational segmentation. Fast and accurate motion segmentation is an important but difficult problem. This is because the images captured in

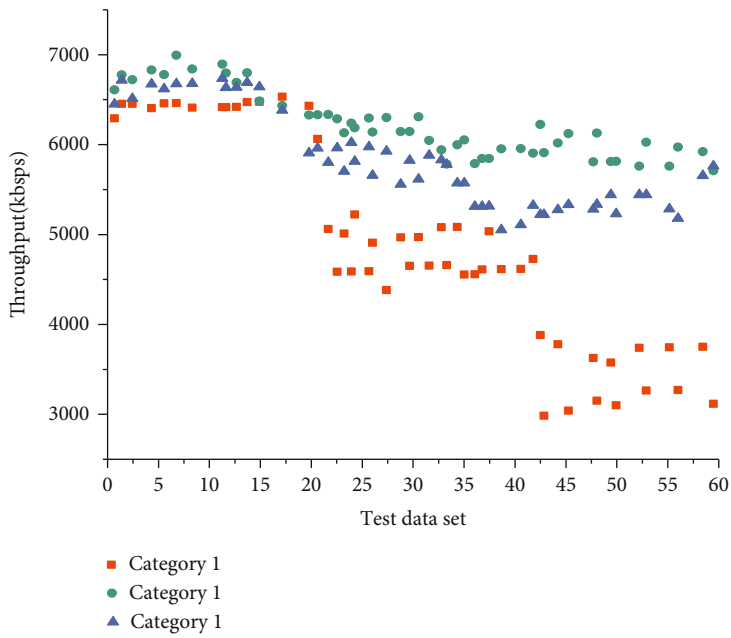

Figure 6: Performance analysis of sports video images under different standards.

the dynamic environment are affected by a variety of factors, such as changes in the weather, changes in the illumination conditions, confusion in the background, and the shadow of the moving target.

The occlusion between the object and environment and between the object and object and even the motion of the camera bring difficulties to accurate and effective motion segmentation. The shadow of a moving target, for example, may be linked to or separated from the target being detected. In the former case, the shadow distorts the shape of the target, which makes the recognition method based on the shape less reliable. In the latter case, the shadow may be mistaken as a completely wrong target in the scene. Although background subtraction is mainly used in image motion segmentation, it is still very difficult to establish a background model that is adaptive to the dynamic changes of any complex environment.

At present, most of the people's motion analysis system cannot solve the problem of close blocking and human self-occlusion. Especially in the state of congestion, the detection and tracking problem of multiple people is difficult to deal with. In occlusion, only part of the human body is visible, and this process is generally not training, and it is simply dependent on the background subtraction. The technique of motion segmentation will not be reliable at this time. In order to reduce the ambiguity problem caused by occlusion or depth, a better model must be developed to deal with the exact correspondence between the features of the occlusion and the body parts. Video object generation has important applications in many aspects. It is not only the base of content-based video coding but also an important link in the video image tracking and recognition system. Because the video object (moving object) exists in the moving change region, one of the important methods of video object generation is to detect the motion change region first and then combine other features to generate the video object in the motion change region. The accurate detection of the motion change region is the key of this method.

6. Conclusions and Future Work

With the rapid development of computer speed and capacity, the application of image technology and machine vision system has made remarkable achievements in recent years, such as content-based image retrieval system, intelligent monitoring system, vision-guided intelligent transportation system, handwritten characters from face grease lines, and iris recognition systems. Image segmentation is an indispensable link in image technology and machine vision and is also one of the bottlenecks in the development of image theory. The research on the image segmentation algorithm has a history of several decades. With the help of various theories, thousands of kinds of segmentation algorithms have been put forward up to now, and only a few years' statistics show that the research on image segmentation still accounts for a large proportion, which shows that image segmentation is still a hot and difficult point. As a key technology in video segmentation, motion change region detection has a direct impact on the accuracy and efficiency of video segmentation, so the research of motion change region detection is of great significance. I will continue to study this key technology with the help of my tutor and experimental group.

Data Availability

All data can be verified by contacting the author.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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