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APPLICATION OF SPORTS VIDEO IMAGE ANALYSIS BASED ON FUZZY SUPPORT VECTOR MACHINE

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Abstract. Sports video image has always been a hot topic in sports video processing. The theoretical and experimental analysis of digital image noise reduction technology is a challenging topic. In this paper, a sports video denoising algorithm is designed by combining the excellent characteristics of curvilinear transformation theory and fuzzy support vector machine. Firstly, the image with noise is curvilinear, and the conversion coefficient is obtained. Then, according to the distribution characteristics of the system noise, the system parameters are divided into space, and the system learning features are constructed. The fuzzy classification of high-frequency curves is realized using the adaptive threshold denoising method. Then, the noise reduction coefficient is reconstructed by the curve-wave method to obtain the processed image. The simulation results show that this method can overcome the pseudo-Gibbs effect effectively and suppress the noise well. This algorithm has a good application prospect in sports video image processing.

Key words: Sports video; Image denoising; Curve-wave transformation; Fuzzy support vector machine; Adaptive threshold

1. Introduction. Image noise reduction is always a hot topic in image processing. Firstly, the image is denoised to provide more accurate information for later image processing (edge detection, object recognition). Second, the development of image noise reduction technology provides a new way for image restoration, image segmentation and other image processing and analysis. In recent years, noise reduction of digital images has become a hot issue in image processing.

The existing denoising methods can be divided into two sides: filter denoising, conditional random field denoising, anisotropic denoising, non-local average denoising and statistical model denoising. The bidirectional filter can eliminate noise and keep boundary information well, but it cannot suppress Speckle noise well and can easily cause excessive smoothness [1]. The feature selection in the conditional random field modelling method has excellent flexibility, and it is unnecessary to give accurate prior data. However, the algorithm faces two difficulties: first, the solution of the energy function of the conditional constraint factor must meet certain conditions, and the global minimization of the conditional constraint factor is an NP-hard problem under most conditions. The second is finding the appropriate energy function to obtain the ideal global minimum [2]. The advantage of the anisotropic diffusion image denoising method is that the image can be denoised without affecting the target features, but this algorithm has some problems, such as over-processing and over-dependence on the target features. Non-local mean methods take advantage of the properties of repetitive structures in the image to remove noise, but their objective quality and visual effect are generally worse than other denoising methods. In recent years, scholars at home and abroad have studied various image noise reduction algorithms based on statistical models [3]. This kind of algorithm mainly uses the inter-scale and intra-scale correlation to reduce noise, but the experiment proves that this kind of algorithm cannot get good noise reduction results.

Sports video is a kind of multimedia data with voice and image as the main content. This data contains some complex semantics. Classification of semantic information in videos is the first step for users to obtain information. Most of the existing video classification methods are for the lower level of image classification, such as shot type, shot action and so on. The use of high-level semantic features can make the classification broader. Some scholars have studied the multi-modal information extraction method. Some scholars classify it according to the rules of basketball [4]. The most significant disadvantage of the lack of semantic guidance for the underlying features is that the moving images cannot be expressed efficiently, and the helpful information

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contained in the moving images cannot be accurately evaluated. For example, the overall feature has a lot of listener noise. Neither from the motion point of view nor from the static point of view can ensure the correct recognition result. There are sports venues, athletes, referees, a large number of spectators and other subjects. Parsing domain rules can obtain the corresponding relationship between low-level attributes and high-level attributes of actions. Therefore, a set of meaningful feature libraries is obtained. This method can effectively classify video objects by an auxiliary classifier.

In this paper, a sports video denoising algorithm is designed by combining the excellent characteristics of curvilinear transformation theory and fuzzy support vector machine [5]. The region features of the target in motion video are obtained by analysing the region boundary and attention mode in motion video. The motion video is classified using a support vector machine (SVM) meta-classifier.

2. Fuzzy support vector machine algorithm.

2.1. Standard Support Vector Machine Algorithm (SVM). The basic idea of SVM is to train the data into nonlinear high-dimensional data. The best categorical hyperplane is constructed in high-dimensional nucleon space, consistent with the VC dimension. The method combines test risk with confidence intervals [6]. The risk classification function with the maximum limit is obtained according to the principle of reducing structural risks to the maximum extent and weighing them. Let the separable sample set be $(u_i, f(u)), i = 1, \cdots, n, u \in R^n, f(u) \in \{+1, -1\}$. The goal of SVM is to create a single-class hyperplane. Separate samples from two different classes to achieve maximum classification spacing. It can get the quadratic optimal problem:

$$\begin{aligned} &\min\left(\frac{1}{2}||\delta||^2 + \lambda\sum_{i=1}^{n} e_i\right) \\ &s.t. \quad f(u)_i[\delta u_i + \sigma] - 1 + e_i \geq 0 \\ &e_i \geq 0 \end{aligned} \tag{2.1}$$

The Lagrange multiplier $\varphi_i (i = 1, 2, \cdots, n)$ is introduced to obtain the duality of the formula:

$$\begin{aligned} &\max\sum_{i=1}^{n}\varphi_i - \frac{1}{2}\sum_{i,j=1}^{n}\varphi_i\varphi_j f(u)_i f(u)_j \mu(u_i, u_j) \\ &s.t. \quad 0 \leq \varphi_i \leq \beta \\ &\sum_{i=1}^{n}\varphi_i f(u)_i = 0 \end{aligned} \tag{2.2}$$

e_i is for the relaxation variable, β represents the penalty factor. $\mu(u_i, u_j)$ is the kernel function. Therefore, the decision function can be obtained as

$$g(u) = sign\left[\sum\nolimits_{i=1}^{n}\varphi_i f(u)_i \mu(u_i, u) + \sigma\right] \tag{2.3}$$

2.2. Multi-classification support vector machine. A multi-class classification method based on SVM is proposed. It can be broadly divided into two categories:

1. One-to-one: SVM classifier is used to learn between two types of samples to obtain samples of $t(t-1)/2$ category. The number of classifiers for each category is $t - 1$. Each classifier decides based on its classification criteria when forecasting a new sample. And vote for the corresponding category. The category with the highest number of votes is the category of the unknown sample.
2. One to many: Support vector machine classification distinguishes each classification from others in order. A total of t classifiers are generated. When forecasting uncertain samples, divide the samples into a class with the maximum determination function value.

If the number of samples is too large, the method's learning efficiency and classification efficiency will be reduced, and both have unidentifiable areas [7]. Then, the improvement method, including ECOC, DAG, etc., is implemented. Choosing the appropriate code book in the ECOC method is a complex problem. There is a shortcoming of the DAG algorithm. Its learning efficiency is not high when dealing with many classes. The selection of the root node significantly influences the classification effect.

2.3. Fuzzy SVM.

2.3.1. Fuzzy SVM Overview. SVM uses the optimal hyperplane to divide data into two opposite categories. In practice, however, each sample cannot be classified into a specific category. Sample and classification have a certain fuzziness. Therefore, many people apply Fuzzy theory to SVM and put forward Fuzzy SVM. This method is an improvement on the classical SVM method [8]. The main idea of this method is to introduce fuzzy theory into the SVM model. The value of the penalty weight varies depending on the size of the sample. In this way, different samples play different roles in the construction process. The sample containing noise or abnormal data is given a low weight to reduce the impact of noise and abnormal data on it.

When using a fuzzy support vector machine for classification, it differs from the traditional support vector machine in the representation of training samples in the following ways: In addition to the characteristics and class recognition of samples, it adds a membership degree to each part of the training. Suppose A training sample set is represented by

$$\begin{aligned}&(u_i, f(u)_i, \eta(u_i)),\\&i = 1, \cdots, n, u \in R^n,.\\&f(u) \in \{+1, -1\}\end{aligned}$$

where $\eta(u_i)$ stands for the degree of subordination and $0 < \eta(u_i) \leq 1$. Because the slave attribute $\eta(u_i)$ represents class confidence. e_i is the category error term in the objective function of SVM. So $\eta(u_i)e_i$ is the error with the weight. The optimal classification surface obtained is the optimal solution of the following objective functions:

$$\begin{aligned}&\min\left[\frac{1}{2}||\delta||^2 + \beta\sum_{i=1}^{n}\eta(u_i)e_i\right]\\&s.t\quad f(u)_i[\delta u_i + \sigma] - 1 + e_i \geq 0\\&e_i \geq 0\end{aligned} \tag{2.4}$$

The Lagrange multiplier $\varphi_i(i = 1, 2, \cdots, n)$is introduced to obtain the duality of the function:

$$\begin{aligned}&\max\sum_{i=1}^{n}\varphi_i - \frac{1}{2}\sum_{i,j=1}^{n}\varphi_i\varphi_j f(u)_i f(u)_j \mu(u_i, u_j)\\&s.t\quad 0 \leq \varphi_i \leq \beta\eta(u_i)\\&\sum_{i=1}^{n}\varphi_i f(u)_i = 0\end{aligned} \tag{2.5}$$

Thus, the decision function is

$$g(u) = sign\left[\sum_{i=1}^{n}\varphi_i f(u)_i \mu(u_i, u) + \sigma\right] \tag{2.6}$$

The comparison of formula (2) and (5) shows that SVM and Fuzzy SVM are different in terms of restrictions. In the SVM model, β is a customizable penalty factor. The algorithm can punish the wrong samples. The more β there is, the heavier the penalty factor. It has an extensive limit system of right and wrong samples and short intervals of class surfaces. When the β value decreases, the SVM will ignore more samples [9]. Thus, a class surface with larger boundary spacing is obtained. Set β more significant in Fuzzy SVM. If all dependencies $\eta(u_i)$ are set to 1, the algorithm reduces the error probability to a normal SVM. In this paper, a fuzzy SVM classification method based on degree $\eta(u_i)$ is proposed to make the classification results more accurate. The lower affiliation has less effect on learning outcomes. Fuzzy SVM has better anti-noise performance than ordinary SVM.

2.3.2. Fuzzy weight calculation. The most crucial thing in using fuzzy technology is determining its attribution function. Different membership degree functions will have different effects on the processing result of the algorithm and the difficulty of the algorithm implementation. Establishing membership functions that can objectively and accurately reflect various uncertainties in the sample is necessary. There is no uniform regulation on establishing membership functions [10]. In practical applications, different problems are often solved from different angles. Many scholars have done some research on this issue. However, most existing FSVM algorithms use the distance from the sample point to the classification center as an evaluation index. More and more people accept this algorithm because of its slight complexity and high robustness. However, in the current fuzzy support vector machine method, the membership degree is mainly measured based on the distance between the sample and the class center. This paper will use the fuzzy membership degree measurement method to determine the fuzzy membership degree $\eta(u_i)$. Set u_0 as the center of the classification. s is the radius of the class representing the system. s is determined by the following formula:

$$s = \max_i ||u_i - u_o|| \tag{2.7}$$

So, the degree of membership of each sample is

$$\eta(u_i) = 1 - \frac{||u_i - u_o||}{s} + \xi \tag{2.8}$$

To prevent the case of $\eta(u_i) = 0$, ξ is pre-set to a tiny constant, ($\xi > 0$).

3. Fuzzy weight calculation. A set of adaptive image noise reduction methods based on Fuzzy SVM is designed, and good noise reduction results are obtained.

3.1. Fuzzy SVM is used for image denoising in the curvilinear wave domain. The working procedure of the classification method based on curve-wave transformation and Fuzzy SVM is as follows:

Step 1. Perform curve-wave processing on noisy images. FTW processing of the original noise image can extract a single low-frequency and several high-frequency bands. The results show that the noise's main component is in the bending region's higher frequency band.

Step 2. Generate feature vectors and train them. The noise distribution and space law characteristics are combined, and the feature vector is constructed [11]. The specific methods are as follows:

(1) The high-frequency subband coefficients of curved waves are initialized with binary tables.

$$\beta_\mu(i,j) = \begin{cases} 1, & |\beta_\mu(i,j)| > \xi \\ 0, & |\beta_\mu(i,j)| \le \xi \end{cases} \tag{3.1}$$

$\beta_\mu(i,j)$ represents the high-frequency subbands in the frequency range of the curve. $\xi = \varphi v + \sigma$ is the threshold function [12]. It is used when building binary tables to select sub-band widths with higher frequencies. v represents the variance of the noise. Where $v = Median(|\beta_t|)/0.6745, \beta_t$ is the maximum subbandwidth of the frequency in the bending frequency range. In addition, several test pictures were used to detect. This paper selected $\varphi = 0.475, \sigma = -3.75$.

(2) Construct a continuous road map and feature vector according to the spatial law. Once the binary table is formed, the function of some high-frequency subbands can be determined according to its spatial distribution law. The coefficient belongs to a subpart of a spatial feature. This paper analyzes the frequency spectrum characteristics of high-frequency signals by the continuous channel method. This is the identification of two high-frequency subbands. If there is a continuous channel between the two, it means that the parameters of the two labeled high-frequency subbands are spatially correlated. After processing the existing data, determine whether each parameter has spatial characteristics and whether each parameter is the noise point [13]. When the continuous path value exceeds a particular threshold value S, it is considered a spatial feature. Otherwise, it is regarded as a noise point.

(3) Select the local High subband coefficient with 0 continuous channels in the most extended continuous channel as the eigenvector.

(4) The obtained feature vectors and labels are used for SVM learning. The training mode of FSVM is obtained by an input feature vector and training sample.

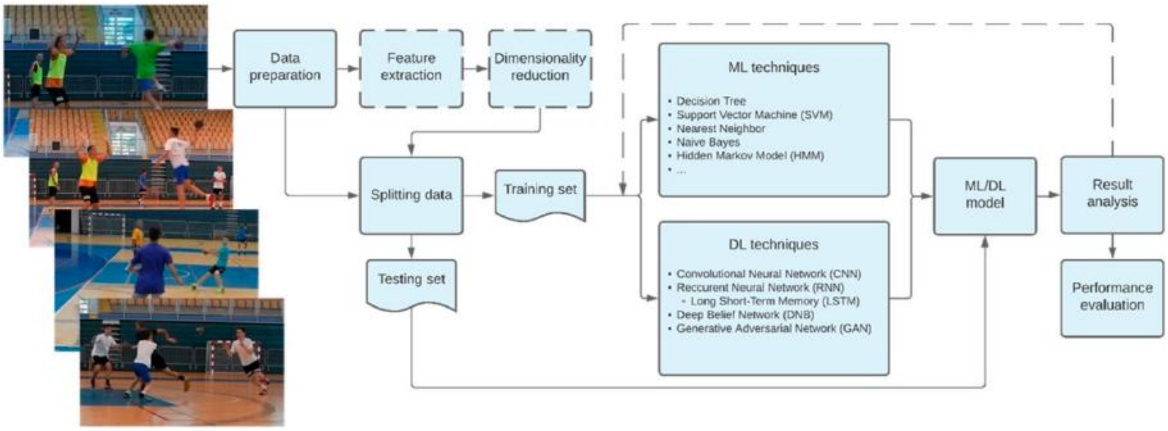

Fig. 3.1: Sports video image processing flow based on fuzzy support vector machine.

Step 3. Remove the high-frequency subband coefficient that contains noise.

Step 4. The fuzzy SVM learning model can divide the high-frequency subband parameters into two types: noisy and noiseless. The output marked 0 of the fuzzy support vector machine training models is set as the noise factor [14]. The output represented by one is noiseless. A noise reduction method based on an adaptive threshold is proposed according to the characteristics of curve wave conversion and the distribution characteristics of noise. Here is the detailed calculation method:

$$S_\mu = \begin{cases} \frac{\hat{v}_\varepsilon^2(\mu)}{\hat{v}_g(\mu)} \frac{1}{\theta_\mu} & \hat{v}_g(\mu) \neq 0 \\ \max(|\beta_\mu(i,j)|) & \hat{v}_g(\mu) = 0 \end{cases} \tag{3.2}$$

S_μ gives the adaptive threshold used for denoising the high-frequency subband coefficients in the K scale and D direction [15]. The local contrast of the image corresponding to the high-frequency subband in the Kscale D direction is expressed by$\theta_\mu.\theta_\mu = \frac{v_\mu}{\mu_\mu}, v_\mu$ represents the variance of the curve's waveform. μ_μ represents the average value of the curve waveform.

$$\hat{v}_\varepsilon(\mu) = Median(|\beta_\mu|)/0.6745 \tag{3.3}$$

The standard deviation of the original image signal is estimated, as shown below

$$\hat{v}_g(\mu) = \sqrt{\max(\hat{v}_\beta^2(\mu) - \hat{v}_\varepsilon^2(\mu), 0)} \tag{3.4}$$

Step 5. Reconstructing the high-frequency subband coefficient using the curve method. The reconstructed noise reduction image can be obtained by calculating the reverse bending wave in the existing high-order frequency band. Fig. 3.1 shows a sports video image's fuzzy support vector machine processing flow.

3.2. The number of categorical characteristics of intervention domain knowledge. The information on sports categories can be normalized at a higher semantic level by extracting the long shot fragments in the pre-processing process [16]. There are pronounced differences among various sports types in the characteristics of the field, the characteristics of the sports object, and the ratio of similar characteristics between the sports field and the sports object. You can see the differences in each feature in Table 3.1 and Figure 3.2.

This paper chooses FAR, MR, MG, MB, VR, VG, VB, NA and AAR as feature vectors. FAR refers to the ratio of the area on the field to the picture. MR, MG, and MB represent the average colour of the field RGB colour space. VR, VG, and VB are the colour variances of the site. The NA value is N (Aa). It refers to the number of contestants. AAR is expressed as S (Aa)/S (F), which is the ratio of the average area occupied by the players to the area of the field and the ratio of the area of the sports field to the screen (FAR) feature has

Table 3.1: The average value of the tuple feature vector.

Category	**Eigenvector mean**								
	FAR	MR	MG	MB	VR	VG	NB	NA	AAR
Soccer	0.921	83.313	103.719	103.656	14.293	69.869	14.454	12.339	0.003
Volleyball	0.347	199.813	100.990	91.594	55.423	15.432	15.845	8.658	0.047
Tennis	0.887	81.615	111.885	169.990	26.367	19.095	45.594	3.243	0.015
Table tennis	0.068	86.844	84.073	175.646	11.701	15.855	65.927	2.408	0.541

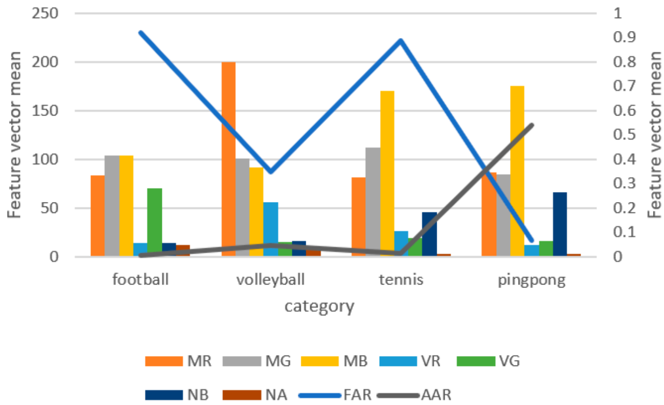

Fig. 3.2: 9 Mean value of tuple feature vector.

a good recognition for games with significant differences in the proportion of the field such as football, hockey and badminton. The venue's colour can make a big difference in outdoor and indoor competitions. Individual sports, such as tennis and rugby, are better distinguished by the characteristics of the crowd and the ratio of the players' pitches ({NA, AAR}) than team sports. Using the SVM method to analyse a 9-tuple vector, most motion videos can be classified and distinguished accurately.

4. Analysis and comparison of experimental results. In this study, football, volleyball, tennis, table tennis, etc., are taken as the research objects, and video collection cards are used to obtain data from TV sets. A picture of a football contains 352x288 pixels. Other video images are 640x480 pixels. The hardware used in the test was a P4-1.4G CPU, a PC with 256 MB of storage space, and a Windows 2016 operating system.

4.1. Feature Extraction. Fig. 4.1 shows the effect of segmenting the arena and players using the method described in Section 1 of this paper. The fields in the video are marked with gray rectangles, while the competitors are marked with a white rectangle. The experimental results show that this algorithm is the most effective for football target detection. The location and size of the players and the course can be marked. In the detection of table tennis, the Gaussian distribution weight is selected to make the central position of the Dalian Tong district more prominent [17]. This is the correct position of the ping-pong ball. The process of a volleyball match is the same as that of a table tennis match. But the method couldn't tell how many people there were, so their portraits had a lot of overlap. The amount of detection area is estimated in the experiment, but the result is unsatisfactory. In the tennis video, the colour of the court and the courtside is similar, resulting in a large screen selection area.

4.2. Classification and classification test of moving images by support vector machine. SVM inputs are based on features in base nine extracted from video clips of football, volleyball, tennis, etc. The relevant parameters of the support vector machine are obtained by cross-checking. After cyclic testing, the final SVM model is obtained. The classification results of four types of video clips are shown in Table 4.1 and Figure 4.2, respectively.

Fig. 4.1: Semantic object detection and segmentation of sports video.

Table 4.1: The average value of the tuple feature vector.

Data set	**Training episodes**	**Number of test sets**	**Cross-validation accuracy / %**	**Test accuracy / %**
Soccer	620	290	98.9	97.4
volleyball	1080	610	98.1	96.8
tennis	419	255	95.4	94.1
Table tennis	910	646	97.4	95.9

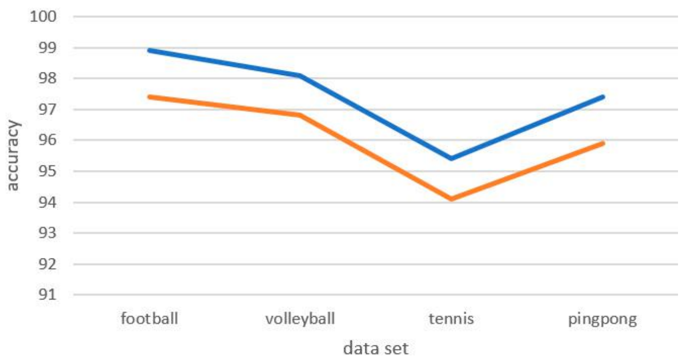

Fig. 4.2: Results of the grading test.

Table 4.2: Comparison of classification results.

Method	**Average accuracy / %**
Semantic feature vector + Fuzzy support vector machine	96.07
Acoustic properties + element hybrid model	88.90
Mobile feature + HMM+ Serial feature strategy	93.98
Action characteristics + speech characteristics + fuzzy matrix + neural network	95.21
Action characteristics + speech characteristics + HMM+ synthesis probability multiplication	95.95

Table 4.2 compares the more commonly used classification methods and classification methods. The experimental results show that the algorithm has a high average accuracy. In addition, the method in this paper can also increase the number of meta-support vector machines to improve the classification of video so that it has better adaptability.

5. Conclusion. A motion video automatic recognition model is established. The existing domain knowledge matches the features and semantics in the image to get the semantic features in the image. Fuzzy SVM is used to reduce the noise of curved waves. A method based on bending waveform is proposed. The spatial characteristics of each parameter are analysed according to the distribution characteristics of noise. The constructed feature vector is input into Fuzzy SVM. The fuzzy classification of high-frequency curves is realized using the adaptive threshold denoising method. Then, inverse curve wave processing obtains the reconstructed image after noise reduction. Experimental results show that the proposed method is superior to the asemantic supervised classification method. This method has good anti-noise performance. Adding a meta-classifier can allow the system to be expanded to classify more kinds of motion video.

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