Fast Recognition of Multi-combination Target Features in Motion Image Based on Large Data Analysis

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Abstract. In order to overcome the low efficiency of traditional recognition technology, a fast recognition method of multi-combination features of moving images based on large data analysis is proposed. Based on feature extraction of multi-combination target, denoising of moving image and determination of Boolean correlation coefficient, fast recognition of multi-combination target feature of moving image under large data analysis is realized. The experimental data show that the proposed recognition method can not only effectively improve the efficiency of traditional recognition technology, but also make the recognition result more stable, and enhance the adaptability and flexibility of image recognition technology.

Keywords: Large data · Motion image · Target feature · Recognition method

1 Introduction

It is of great significance to classify multi-combination targets of moving images and recognize them in the practice of national defense and modernization construction. In this paper, a recognition method of multi-combination target features in moving images is proposed. Because there are many kinds of target features, the appropriate feature set should be selected according to the empirical evidence of different kinds of typical performance. If the selected feature set can not obtain the effective information of the target to be identified, the feature information should be re-selected. There are many traditional image classification methods, such as statistical classification method, The K-means algorithm, K-Means algorithm, CART classification and regression tree algorithm, but these methods are powerless for high-dimensional and massive classification and recognition problems. In this paper, the PSO algorithm of large data neural network is used for noise reduction, and the fast recognition of multi-combination target features in moving images is realized by the calculation of Boolean correlation.

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2 Fast Recognition of Multi-combination Target Features in Motion Image Based on Large Data Analysis

2.1 Feature Extraction of Multi-combination Objects in Image

The structure of the image affects the result of feature extraction of multi-combination targets. Most of the methods of feature extraction of multi-combination targets are based on the surface and local information of the image. The feature information extraction method based on multi-color features uses multi-color features of the image, divides the image according to the color features, and then uses discrete statistical processing fitting technology to reconnect the segmented regions, completing the process of extracting the feature information of the image.

Firstly, the multi-color features of the image are classified. In the Lab color channel, the brightness, color, texture and other color features are extracted, and then the color features of the image are segmented. Secondly, the segmented image blocks are represented by color feature difference:

$$x^2(g,h) = \frac{1}{2}\sum_i \frac{(g(i)-g(h))^2}{g(i)+g(h)} \tag{1}$$

In the formula, g and h represent the color features of the recognized image. After calculation, the feature information of the image is extracted. The method of feature extraction of multi-combination targets in images is greatly influenced by the intensity of illumination. It is also necessary to use the edge detection algorithm based on mathematical morphology to extract the secondary feature information of images. Firstly, the geometric model of mathematical morphology recognition is constructed to obtain the geometric feature information of the image. Then, feature information matching is carried out based on mathematical morphology extraction method.

In the least squares format, $z(k) = h^{\tau}(k)\theta + n(k)$ and $\theta = [a_1, a_2, \ldots a_{n_a}, b_1, b_2, \ldots, b_{n_b}]^{\tau}$ are the parameters to be estimated. $h(k) = [-z(k-1), \ldots, -z(k-n_a), u(k-1), \ldots, u(k-n_b)]^{\tau}$, for $k = 1, 2, \ldots L$ (L is the length of the data). Construct a system of linear equations, written in $z_L(k) = H_L(k)\theta + n_L(k)$;

$$Z_L = \begin{bmatrix} z(1) \\ z(2) \\ \vdots \\ z(L) \end{bmatrix}, H_L = \begin{bmatrix} h^{\tau}(1) \\ h^{\tau}(2) \\ \vdots \\ h^{\tau}(L) \end{bmatrix}, n_L = \begin{bmatrix} n(1) \\ n(2) \\ \vdots \\ n(L) \end{bmatrix} \tag{2}$$

According to the least square method, the parameters of the algorithm are estimated as follows: $\hat{\theta}LS = (H_L^{\tau}H_L)^{-1}H_L^{\tau}Z_L$.

The steps of image multi-combination target feature are as follows:

Step 1: Initialize $W(0) = 0$; $P(0) = \sigma^{-1}I$, where I is the unit matrix;

Step 2: Update $n = 1, 2, \ldots$ Calculation;

Update the gain vector: $g(n) = P(n-1)X(n)/[\lambda + X^T(n)P(n-1)X(n)]$ Extraction: $y(n) = W^T(n-1)X(n)$;

Error estimation: $e(n) = d(n) - y(n)$;

Update the weight vector: $W(n) = W(n-1) + g(n)e(n)$;

Update the inverse matrix: $P(n) = \lambda^{-1}[P(n-1) - g(n)X^T(n)P(n-1)]$. Among them, $P(n)$ is the inverse of the autocorrelation matrix $P_{xx}(n)$, constant λ is the forgetting factor, and $0 < \lambda < 1$.

In summary, according to data acquisition and generation, take $d(n)$, $X(n)$; initialization of parameters; extraction and processing of multi-combination target features of images; conversion of images into digital images; HMT transformation of recognized images. After HMT transformation of images, geometric correspondence can be established between recognized images and digital images. Finally, the task of extracting information from the target image is completed.

2.2 Noise Reduction Processing of Motion Image

In motion image denoising, PSO algorithm based on large data neural network is used to denoise. Big data neural network is a multi-layer network with one-way propagation. It has three layers: input layer, hidden layer and output layer [1], which are divided into forward and backward propagation. The weights of each layer are adjusted by forward and backward propagation errors. The process of weights adjustment is the training process of the neural network, which reduces the output errors and is used for noise reduction. This process is cyclical until the termination condition is reached. Figure 1 is a schematic diagram of denoising processing of large data neural network.

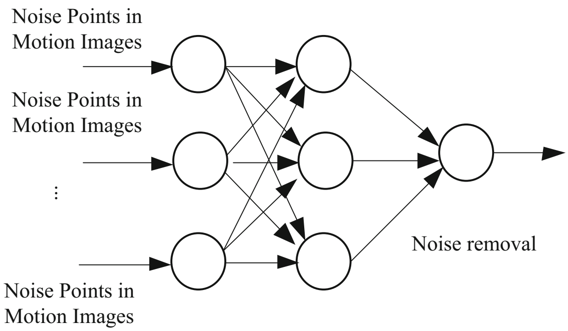


Fig. 1. Large data neural network denoising processing

In order to achieve image denoising of multiple combined targets in moving images, 15 nodes are selected in the input layer, including 12 time points data and 3 Influence Factors normalized and quantified data.

Write it down as xk = (xk1, xk2,… XKH,… Xk15) the output layer has one node, which is represented by empirical formula $m = \sqrt{n + l} + a$, M represents the number of nodes in the hidden layer, n represents the number of nodes in the input layer, l represents the number of nodes in the representative layer, and a takes the constant between 1 and 10. Considering the accuracy of the results, the number of nodes is 5, 6 and 7, and the number of nodes in hidden layer is 6 [2].

The transfer function between the hidden layer and the output layer is bipolar S-type function $f(x) = \frac{2}{1-e^{-x}} - 1 = \frac{1-e^{-x}}{1+e^{-x}}$. The weight matrix between the input layer and the hidden layer is expressed by v. The weight matrix from the hidden layer to the input layer is expressed by W. For the hidden layer, there are $y_i = f(net_j),\ j = 1, 2, \ldots, w,\ \ net_i = \sum_{i=0}^{n} v_{ij} x_i,\ j = 1, 2, \ldots, w$. For the output layer, there are $O_k = f(net_k),\ \ j = 1, 2, \ldots, m,\ net_j = \sum_{i=0}^{n} v_{jk} x_i,\ j = 1, 2, \ldots, w$.

Suppose the position Y and velocity V of the i particle are $Y_i = (Y_{i1}, Y_{i2}, \ldots, Y_{in}),\ V_i = (V_{i1}, V_{i2}, \ldots, V_{in})$, respectively. The historical optimal solution of the i particle is $P_i = (P_{i1}, P_{i2}, \ldots, P_{in})$, the optimal solution of the particle swarm is $P_m = (P_{m1}, P_{m2}, \ldots, P_{mn})$, and the velocity and position of the particle are updated as follows [3, 4]:

$$\begin{cases} V_{in}(t+1) = wv_{in}(t) + c_1 r_1 (P_{in} - x_{id}(t)) + c_2 r_2 (P_{mn} - x_{in}(t)) \\ \quad Y_{in}(t+1) = Y_{in}(t) - V_{in}(t+1) \end{cases} \tag{3}$$

In the formula, W is called inertia factor, the range of values is [0.4, 0.9]; c1, C2 is noise factor, the value is 2. R1 and R2 are random numbers distributed in [0,1].

The PSO algorithm of large data neural network is used to automatically adjust the parameters of image extraction to adapt to the statistical characteristics of unknown signals and noises or changing with time, so as to achieve the optimal extraction.

The PSO algorithm of large data neural network is essentially an adaptive extraction algorithm which can adjust its transmission characteristics to achieve the optimal.

In the running process of particle swarm optimization in big data neural network, adaptive digital extraction with adjustable parameters is generally called FIR digital adaptive extraction, also known as dot matrix digital adaptive extraction. On this basis, the particle swarm optimization algorithm of big data neural network can be divided into two processes.

Firstly, after the input signal adjusts x (n) to digital adaptive signal through parameters, the output signal Y (n), y (n) is compared with the reference signal D (n) to get the error signal e (n) [5]. Secondly, the parameters are adjusted by an adaptive algorithm and the values of X (n) and E (n). The input signal x (n) is weighted to the digital adaptive output signal Y (n). The adaptive algorithm adjusts the extraction weight coefficient to minimize the error signal e (n) between the output y (n) and the adaptive extraction expected response D (n).

The PSO algorithm coefficients of large data neural networks are controlled by error signals, and are automatically adjusted according to the value of E (n) and the adaptive algorithm. By adjusting the weight coefficient, the mean square error between the adaptive extracted output signal Y (n) and the expected response signal D (n) is minimized, or $e^2(n)$.

$$\overset{\wedge}{\nabla}(n) = \frac{\partial[e^2(n)]}{\partial w(n)} = -2e(n)x(n) \tag{4}$$

This instantaneous estimation method is unbiased because its expected value E[$\overset{\wedge}{\nabla}(n)$] equals vector $\nabla(n)$. Therefore, according to the relationship between the variation of coefficient vectors and the direction of gradient vector estimation extracted by PSO algorithm of large data neural network, we can first write the formula of PSO algorithm of large data neural network as follows:

$$\hat{w}(n+1) = \hat{w}(n) + \frac{1}{2}\mu[-\overset{\wedge}{\nabla}(n)] = \hat{w}(n) + \mu e(n)x(n) \tag{5}$$

By substituting the formulas e(n) = d(n)–y(n) and e(n) = d(n)–wHx(n) into the formulas above, we can get:

$$\begin{aligned}\hat{w}(n+1) &= \hat{w}(n) + \mu x(n)[d(n) - \hat{w}^H(n)x(n)] \\ &= [I - \mu x(n)x^H(n)]\hat{w}(n) + \mu x(n)d(n)\end{aligned} \tag{6}$$

The denoising of moving image is realized.

2.3 Fast Recognition of Target Characteristics

In order to realize the fast recognition of image target, statistical analysis should be carried out from the Angle of moving image data station, and then the fast recognition function of target should be completed by summarizing and processing data set, eliminating mixed data and calculating data.

The fast recognition algorithms for target features can be divided into the following categories:

The K-means algorithm, K-Means calculation theory, Support Vector Machines, The Apriori algorithm, Boolean association rule frequent iteration calculation theory, and Adaboost iteration calculation theory.

Based on the theory of strategy tree and Boolean association rule frequent itemset, a motion image guidance algorithm is constructed. It is applied to fast recognition of target features in moving images.

Boolean association rule frequent itemset computing theory is a big data computing theory of probability correlation statistics. Based on the statistical method of frequent itemsets of association rules published by James Boole in statistical, and the continuous optimization of the algorithm of large data of association statistics by mathematicians represented by Egstrom, the Boolean association rule frequent itemset computing theory is established [6]. Boolean Association Rules Frequent Item Set Computing Theory is a mathematical large data computing method suitable for data statistical recognition and mining [7]. Let there be a set of target characteristic variables A = {A1, A2,… An}, where the data of variable set A satisfies a certain recognition trend relation D and the local variables conform to the correlation probability distribution R, then a recognition trend network can be formed. The sketch diagram of the recognition trend network is shown in Fig. 2 [8].

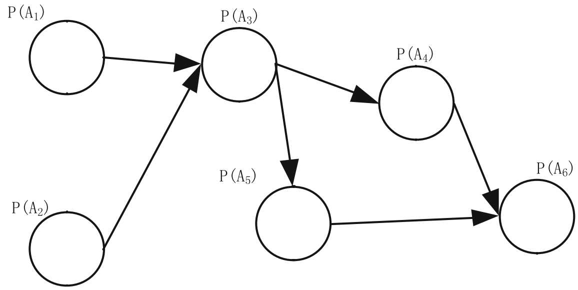


Fig. 2. Identifying trend network diagram

In Fig. 2, A1 and A2 represent target features to quickly identify user behavior, D represents causality, R represents correlation probability distribution, and A3 represents self-Media recognition trend. At the same time, derivatives can be calculated according to operation A3, and derivatives of identification can be inferred to calculate A4 and A5, and conclusion A6 can be drawn. Its derivative calculation satisfies the following formula [9, 10]:

$$C = \sigma_o \gamma_i + W_0 (\partial^2 q_k dx)/S \tag{7}$$

From formula (7), the value of Boolean correlation coefficient will directly affect the accuracy of user behavior estimation results A4 and A5. At the same time, the response time of accurate Boolean correlation coefficient will directly affect the speed of large data analysis. The selection of Boolean correlation coefficient is related to causality D and probability distribution R, which satisfies the relationship in Table 1.

Table 1. Selection of boolean correlation coefficient

Causality D	Probability distribution R	Boolean coefficient S
[0.00,0.30]	[0.00,0.50]	[0.00,0.45]
[0.30,0.50]	[0.00,0.50]	[0.45,0.62]
[0.50,0.80]	[0.50,1.00]	[0.62,0.83]
[0.80,1.00]	[0.50,1.00]	[0.83,1.00]

In order to obtain the Boolean correlation coefficient quickly, the causality D and the probability distribution R are determined firstly, then the range of the Boolean correlation coefficient is determined according to Table 1, and then the specific value of the Boolean correlation coefficient is determined according to Egstrom function, which greatly saves the time of obtaining the Boolean correlation coefficient directly by Egstrom calculation.

Based on the Boolean correlation coefficient, the threshold function is used to compute the target features. In the image with an indivisible target feature subset, when the distance between the two target feature subsets is long enough, the two subsets can be segmented by using the linear function relationship. However, when the two subsets are close to each other, the Kmean ++ algorithm is used to discretize the extracted image, and then the importance SGA of the target eigenvalues of the two subsets is calculated. Finally, the attributes with small importance of the target eigenvalues are selected as the image segmentation points for segmentation. However, when the two subsets are close to each other, the Kmean ++ algorithm is used to discretize the extracted image, and then the importance SGA of the target eigenvalues of the two subsets is calculated. Finally, the attributes with small importance of the target eigenvalues are selected as the image segmentation points for segmentation [11, 12].

Then the undivided image is segmented from the important points by the same method, and the decision tree is generated. After two segmentation, two recognition results will be produced. Thirdly, Kmean ++ algorithm is used to discretize the original image, randomly select points on the recognized image, and then form a discrete sequence, which is segmented several times, and the recognition results are processed by discrete statistics, finally the image recognition is completed.

3 Simulation Experiment and Result Analysis

In order to verify the practical application performance of the above moving image multi-combination target feature recognition method based on big data analysis, the following simulation experiment is designed for verification.

In the simulation experiment, the recognition effect of the traditional image recognition technology and the moving image multi-combination target feature recognition method based on big data analysis is compared. The experimental data are from the ImageNet data set. In order to ensure the accuracy of simulation test, many simulation tests are carried out, and the data generated by the tests are displayed in the same data graph.

3.1 Experimental Data Setting

In order to ensure the accuracy of the simulation test process and results and set the test parameters, 120 multi-combination target images of different kinds of moving images were browsed by two image recognition technologies. Among them, there are 30 moving images of people, 30 moving images of cars, 30 moving images of aircraft and 30 moving images of animals. Five images are randomly extracted from each image classification, totaling 20 images. Two different image recognition techniques are used to identify and classify them.

3.2 Analysis of Experimental Results

The experimental results are counted into Table 2. It can be seen from Table 2 that the method in this paper can effectively improve the recognition rate of images, and the number of effective recognition is significantly higher than that of traditional methods. Moreover, the fast recognition method based on big data analysis for multiple target features of moving images is more efficient in recognizing animal moving images and aircraft moving images.

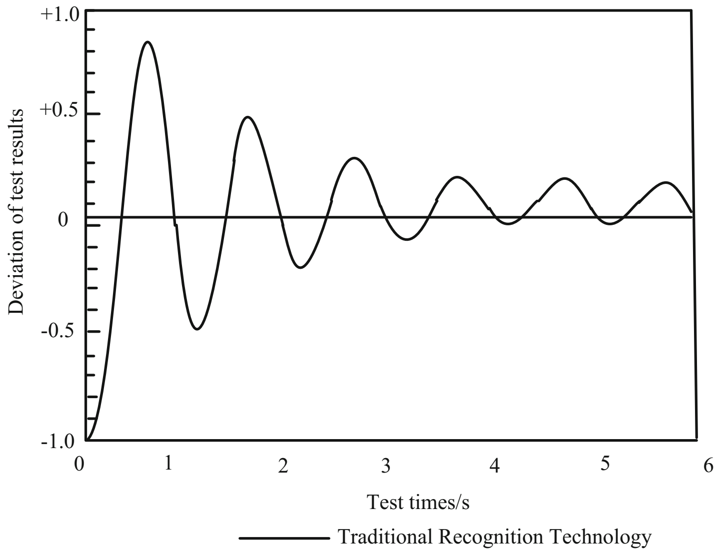
Table 2. Experimental results of two recognition techniques

Technology category	Image class	Number of valid identification	Effective recognition rate
Traditional image recognition technology	Character motion images	4	80%
	Animal motion images	3	60%
	Aircraft motion image	1	20%
	Automatic generation of portraits	5	100%
Image recognition technology based on artificial neural network	Character motion images	4	80%
	Animal motion images	4	80%
	Aircraft motion image	4	80%
	Automatic generation of portraits	5	100%

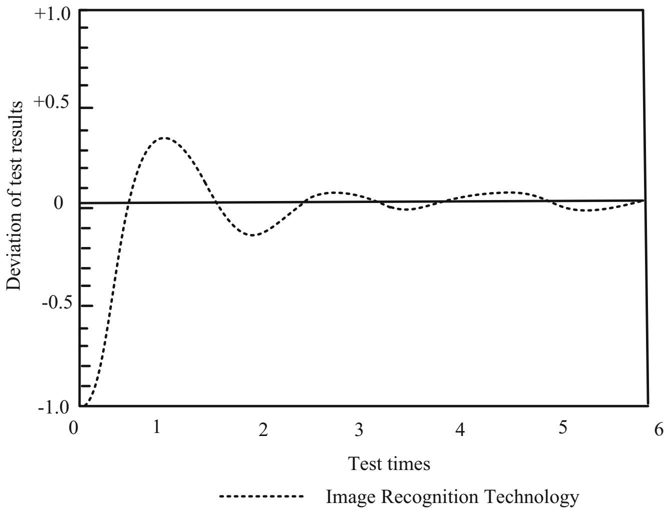
In the experimental process, if the number of random sampling is small, the deviation of test results will be caused. After many times of extraction and recognition experiments, the effective recognition efficiency of the two recognition technologies has changed. The recognition result deviation of the two recognition technologies is shown in Fig. 3.

From the analysis of Fig. 3, it can be seen that the stability of the recognition method designed in this paper is higher than that of the traditional image recognition technology, and the deviation of the recognition result is not only small but also stable.

To sum up, the fast recognition method of moving image multi-combination target features designed in this paper based on big data analysis can not only effectively



(a)Traditional Recognition Technology



(b)Image Recognition Technology

Fig. 3. Comparison of deviation between two recognition techniques

improve the recognition efficiency and accuracy, but also make the recognition results more stable and enhance the adaptability and flexibility of the image recognition technology.

4 Conclusion

Target recognition is a key problem in multi-combination target interpretation of moving images. It has the characteristics of large amount of computation and long time-consuming. In order to speed up multi-combination target recognition of moving images. In this paper, the PSO algorithm of large data neural network is used for noise reduction, and the fast recognition of multi-combination target features in moving images is realized by the calculation of Booleancorrelation. The experimental results show that the method has strong anti-noise performance, is effective in extracting multi-combination features of target moving images, fast in training and recognition, and has high recognition efficiency. It is suitable for multi-combination target recognition of moving images in low signal-to-noise ratio images. The further work is to study the performance and improvement of the algorithm in the case of complex background or target missing.

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