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Minority Costume Image Retrieval by Fusion of Color Histogram and Edge Orientation Histogram

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Abstract

It has very important practical significance to analyze and research minority costume from the perspective of computer vision for minority culture protection and inheritance. As first exploration in minority costume image retrieval, this paper proposed a novel image feature representation method to describe the rich information of minority costume image. Firstly, the color histogram and edge orientation histogram are calculated for divided sub-blocks of minority costume image. Then, the final feature vector for minority costume image is formed by effective fusion of color histogram and edge orientation histogram. We have evaluated the performances of the proposed algorithm on self-build minority costume image dataset, and the experimental results show that our method can effectively express the integrated feature of minority costume images, including color, texture, shape and spatial information. Compared with some conventional methods, our method has higher and stable retrieval accuracy.

Keywords: Color Histogram; Edge Orientation Histogram; Minority Costume; Image Retrieval.

1. Introduction

China is a country consisting of 56 ethnic groups, and each of them has its own apparel style with distinct ethnic characteristics, due to the influence of different culture, traditions, and geographical feature. The minority costume is an important symbol of the ethnic group identification and the precious wealth of the Chinese nation. However, with the acceleration of global economic and political integration in China, various minority costume cultural traditions have been rapidly disappearing. This prompted people to think the survival of minority costume under the new historical situation. For now, the minority costumes are mainly protected by museums statically. Compared with the traditional protection mode of physical originals in museums, digital protection has longer protection time and promotes minority costume culture more conveniently. Content-based image retrieval is a very important topic in the field of pattern recognition and artificial intelligence. It has been successfully applied to many fields, such as medical diagnosis, textiles industry and so on. The minority costume of same nation have their own distinguished characters (unified tone, style and patterns.), which make them more advantageous than ordinary natural images in image processing. Therefore, it is of great importance to analyze the visual features of minority costumes. In this paper, the digital protection of national costume is studied from the perspective of computer vision.

Although national minority clothing image have complex visual features, the main characteristics still are clothing color, fabric texture and totem shape, which are in accordance with the image feature in computer vision. So we can use traditional feature extraction algorithms to extract the features of minority costume images. At present, a large number of approaches on extraction of color, texture and shape features have been put forward and have already obtained good results in many fields. Color is the most dominant and distinguishing visual feature. The existing color feature extraction methods include color histogram [1], color moment [2], color coherence vector [3] and color correlogram [4]. Texture is used to specify the roughness or coarseness of object surface and described as a pattern with some kind of regularity. Many researchers have put forward various algorithms for texture analysis, such as the famous gray level co-occurrence matrix (GLCM) [5], local binary patterns (LBP) [6], local directional patterns (LDP) [7], and so on. Shape is the most essential feature of the object. The classic shape descriptors are the Hu moment invariants [8], the Fourier transform coefficients [9] and the histogram of oriented gradients (HOG) [10].

The minority costume image have very complex visual features, which make it more difficult to be expressed by single feature extraction algorithm. So our goal is to design a feature extraction algorithm based on multi-features to express the information of minority image comprehensively. Many image feature extraction algorithms based on multi-features have been proposed in recent years. In 2010, Guang-Hai Liu proposed a novel image feature representation method, called multi-texton histogram [11], for image retrieval. It integrates the advantages of co-occurrence matrix and histogram by representing the attribute of co-occurrence matrix using histogram. Micro-structure descriptor [12] proposed by Guang-Hai Liu in 2011 is built based on the underlying colors in micro-structures with similar edge orientation. Guang-Hai Liu also proposed color difference histogram [13] in 2013, which count the perceptually uniform color difference between two points under different backgrounds with regard to colors and edge orientations in L*a*b* color space. The image feature extraction algorithms mentioned above have all achieved high retrieval accuracy in Corel image database [14].

In view of many image feature extraction algorithms based on multi-features have been successfully applied in image retrieval, this paper presents a comprehensive feature descriptor to express the rich visual features presented in minority costume image. This descriptor is represented by effective fusion of color histogram and edge orientation histogram. It's implied in experimental results that the image representation techniques used in our method are an effective way of integrating low-level features into a whole.

2. Related Works

Currently, the research work of minority costume image retrieval is still in its infancy and exploration stage. We are the first ones to conduct exploratory research on the retrieval technology of minority costume image. In this paper, we construct a minority costume image dataset, in which some images are taken by ourselves and some are from the internet. Most of the minority costumes in these images are dressed by minority people or human body model, and some are photographs of tiled minority costumes. Every ethnic group has its own costume style, so we can distinguish between ethnic groups by their costumes. After a series of researches on the characteristics of minority costumes in Yunnan, we choose the six most characteristic ethnic groups' costume as the research object, including Bai nationality, Jingpo nationality, Hani nationality, Miao nationality, Bouyei nationality and Va nationality. For each nationality we collect 100 costume images and preprocess them to size 128×96 or 96×128 in JPEG format. Figure 1 shows some image examples in the minority costume image dataset.

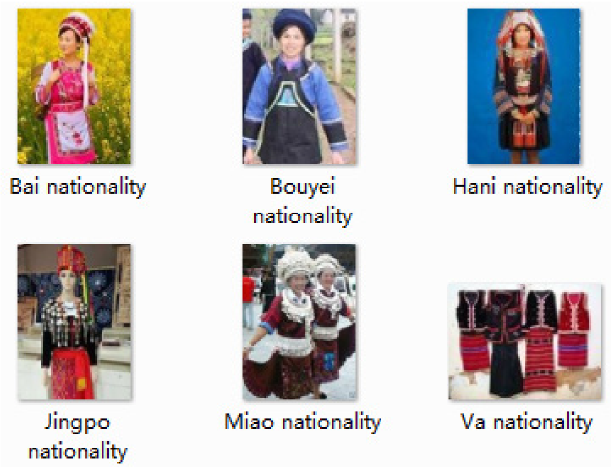

Fig.1. An example of the minority costume image dataset

For now, no researcher has conducted exploratory research on the retrieval technology of minority costume image. Nevertheless, many scholars have researched on the image processing technology of ordinary clothing image from the perspective of computer vision. Choi Yoo-Joo [15] presents a novel approach to retrieval the person image that contain the identical clothing to a query image from the image set captured by multiple CCTV camera. Wang Hai-long

[16] presents a method of contour feature extraction, expression and matching to implement clothing image retrieval comprehensively, where the clothing image is from e-commerce websites. Chen jia-lin [17] presents an interactive clothing retrieval system, which supports query by a real-world image with target clothing and returns real-world images with similar clothing. Wang Yatong [18] designs and implements an image querying and retrieval system based on color feature for e-commerce apparel.

3. Feature extraction of minority costume image

3.1. Calculation of Color Histogram

The color histogram is one of the most direct and the most effective color feature representation [19]. But it lacks spatial information. This paper incorporates spatial information to it by combining the color histograms for several sub-blocks defined in the minority clothing image. An appropriate color space and quantization must be specified along with the histogram representation. In this paper, three color spaces (RGB, HSV and CIE L*a*b*) with different quantification number are used to test the performance of our Method. The experimental results in Tables 1-3 demonstrate that the RGB color space with 8×4×4=128 quantification number is the best choice in our framework. For an image with a size of *M*×*N*, we set the color quantification number to L and denote the image by the equation $C(x,y),(x\in[0,N),\ y\in[0,M))$. The value range of $C(x,y)$ is $[0,L)$. We divide the image to n blocks. The color values of each block is denoted by $C_i(x,y),(i\in[0,n))$, then the color histogram of each block is defined as:

$$\mathrm{H}_{C_i(x,y)}(j)=num_j,(j=0,1,...,L-1) \tag{1}$$

where num_j is the number of pixels in a sub-block whose color value is quantified to *j*.

3.2. Calculation of Edge Orientation Histogram

In the system of theory on computer vision, edge detection of image plays an important role. This paper construct a feature descriptor namely edge orientation histogram, which can be seen as a texture feature and also a shape feature. The classic edge detection operator are Sobel, Roberts, Prewitt and Canny. Sobel is one of the most popular operator [20], which is based on convolving the image with a small, separable, and integer valued filter in the horizontal and vertical directions and is therefore relatively inexpensive in terms of computations. The operator uses two 3×3 kernels which are convolved with the original image to calculate approximations of the derivatives - one for horizontal changes, and one for vertical. If we define R, G, B as the unit vectors along the R, G, B axes in RGB color space, the computations are as follows:

$$g_{Rx}=\begin{bmatrix}-1&0&1\\-2&0&2\\-1&0&1\end{bmatrix}\times R, g_{Gx}=\begin{bmatrix}-1&0&1\\-2&0&2\\-1&0&1\end{bmatrix}\times G, g_{Bx}=\begin{bmatrix}-1&0&1\\-2&0&2\\-1&0&1\end{bmatrix}\times B \tag{2}$$

$$g_{Ry}=\begin{bmatrix}1&2&1\\0&0&0\\-1&-2&-1\end{bmatrix}\times R, g_{Gy}=\begin{bmatrix}1&2&1\\0&0&0\\-1&-2&-1\end{bmatrix}\times G, g_{By}=\begin{bmatrix}1&2&1\\0&0&0\\-1&-2&-1\end{bmatrix}\times B \tag{3}$$

g_{xx}, g_{yy} and g_{xy} are defined as dot products of the vectors mentioned above:

$$g_{xx}=g_{Rx}^2+g_{Gx}^2+g_{Bx}^2 \tag{4}$$

$$g_{yy}=g_{Ry}^2+g_{Gy}^2+g_{By}^2 \tag{5}$$

$$g_{xy}=g_{Rx}\times g_{Ry}+g_{Gx}\times g_{Gy}+g_{Bx}\times g_{By} \tag{6}$$

Using the above notations, it can be seen that the maximum gradient orientation of point (x,y) is

$$\varphi(x,y)=\frac{1}{2}\arctan(\frac{2g_{xy}}{g_{xx}-g_{yy}}) \tag{7}$$

And the gradient magnitude at (x, y) in the direction of $\varphi(x,y)$ given by

$$G(x,y)=\left\{\frac{1}{2}\left[(g_{xx}+g_{yy})+(g_{xx}-g_{yy})\cos 2\varphi+2g_{xy}\sin 2\varphi\right]\right\}^{1/2} \tag{8}$$

Because $\tan(\alpha)=\tan(\alpha\pm\pi)$, if φ_0 is a solution to Eq. (7), the $\varphi_0\pm\pi/2$ will be a solution, too. Furthermore, $G_\varphi=G_{\varphi+\pi}$; therefore, $G(x,y)$ has to be computed only for values of φ in the half-open interval $[0,\pi)$. Because Eq. (7) provides two values 90° apart, this equation associates a pair of orthogonal directions with each point (x,y):

$$G_1(x,y)=\left\{\frac{1}{2}\left[(g_{xx}+g_{yy})+(g_{xx}-g_{yy})\cos 2\varphi_0+2g_{xy}\sin 2\varphi_0\right]\right\}^{1/2} \tag{9}$$

$$G_2(x,y)=\left\{\frac{1}{2}\left[(g_{xx}+g_{yy})+(g_{xx}-g_{yy})\cos 2(\varphi_0+\pi/2)+2g_{xy}\sin 2(\varphi_0+\pi/2)\right]\right\}^{1/2} \tag{10}$$

In practical applications, the maximum of the gradient direction is taken. Thus, we can denote the gradient direction $\varphi(x,y)$ as follows:

$$\varphi(x,y)=\begin{cases}\varphi_0 & if\ \max(\mathrm{G}_1,G_2)=G_1(x,y)\\ \varphi_0+\pi/2 & if\ \max(\mathrm{G}_1,G_2)=G_2(x,y)\end{cases} \tag{11}$$

To facilitate implementation, we project it into the interval $[0,2\pi]$. After the edge orientation $\varphi(x,y)$ of each pixel has been computed, the orientations are uniformly quantized into m bins, where $m = 12, 18, 24, 30, 36$. Data in Tables 1-3 show that the 30 bins used in the RGB color space are more suitable for our framework. We use histogram of edge orientation to represent the feature of minority costume image. Because histogram is lack of the spatial position information of the image. Therefore, in this paper, before the extraction of edge orientation histogram feature, we divide the minority costume image with a size of $M\times N$ into n sub-blocks first. The edge orientation values of each block is denoted by $\varphi_i(x, y), (i \in [0, n))$, then the edge orientation histogram of each block is defined as follows:

$$\mathrm{H}_{\varphi_i(x,y)}(j) = num_j, (j = 0, 1, ..., m-1) \quad (12)$$

where num_j is the number of pixels in a sub-block whose orientation value is quantified to j.

3.3. Comprehensive feature representation

The comprehensive feature extraction algorithm proposed in this paper can be represented as follows:

Step1: Divide the minority costume image with a size of $M\times N$ into n sub-blocks, the experimental results in Table 4 demonstrate that our method gets the best results when n=2×2.

Step2: Calculate the color histogram of every sub-block and then linearly combine them as $\mathrm{H}_{C(x,y)}=[\mathrm{H}_{C_1(x,y)}, \mathrm{H}_{C_2(x,y)}, ..., \mathrm{H}_{C_n(x,y)}]$.

Step3: Calculate the edge orientation histogram of each sub-block and then linearly combine them as follows:

$$\mathrm{H}_{\varphi(x,y)} = [\mathrm{H}_{\varphi_1(x,y)}, \mathrm{H}_{\varphi_2(x,y)}, ..., \mathrm{H}_{\varphi_n(x,y)}] \quad (13)$$

Step4: Linearly Combine all the histograms mentioned in step2 and step3 as $\mathrm{H}=[\mathrm{H}_{C_i(x,y)}, \mathrm{H}_{\varphi_i(x,y)}], (i \in [0, n))$.

3.4. Similarity measurement

After feature extraction, each image in the minority costume image dataset can be represented by a multidimensional feature vector $\mathrm{H}=[\mathrm{H}_{C(x,y)}, \mathrm{H}_{\varphi(x,y)}]$. If we use CSA and CSB to represent the dimension of color histogram $\mathrm{H}_{C(x,y)}$ and the dimension of edge orientation histogram $\mathrm{H}_{\varphi(x,y)}$ respectively, a $M = CSA + CSB$ dimensional feature vector will be extracted and stored for every image in the image dataset. Let $H(Q) = [H_1(Q), H_2(Q), ..., H_M(Q)]$ and $H(T) = [H_1(T), H_2(T), ..., H_M(T)]$ be the feature of query image Q and image T in the database. Then the retrieval results can be returned by computing a similarity measure of feature vector between query image and every image in the dataset. There are many distance metrics for similarity measure, like Manhattan distance, Euclidean distance, Chi Square distance, Canberra distance etc. The experiment results in Table 6 show that Canberra distance [21] is a better distance metric for our method than others. This paper improve the Canberra distance by introducing a parameter λ :

$$D(Q,T) = \lambda \sum_{i=1}^{CSA} \frac{|H_i(Q) - H_i(T)|}{1 + H_i(Q) + H_i(T)} + (1-\lambda) \sum_{j=1}^{CSB} \frac{|H_i(Q) - H_i(T)|}{1 + H_i(Q) + H_i(T)} \quad (14)$$

where $H_i(Q)$ is the i^{th} feature of query image Q, $H_i(T)$ is the i^{th} feature of target image T in dataset.

4. Experiments and results

In this section, we evaluate the performance of our method by using the minority costume image dataset described in section 2. The precision and recall curves are adopted to evaluate the effectiveness of our method, which are the most common measurements used for evaluating image retrieval performance. Precision and Recall are defined as follows:

$$\mathrm{Precision} = I_N / N \quad (15)$$

$$\mathrm{Recall} = I_N / M \quad (16)$$

where I_N is the correct number of images retrieved in the top N positions that are similar to the query image, M is the total number of images in the database similar to the query, and N is the total number of images retrieved. In our image retrieval system, N=12 and M=100.

4.1. Experiment 1

Obviously, the quantization number of color and edge orientation all have direct influence on the formation of image feature in according to the description in section 3. So different quantization numbers for color and edge orientation are used to test the performance of the proposed method (with 2×2=4 sub-blocks and λ=0.5) in the L*a*b*, RGB and HSV color spaces. The values of precision and recall with the top 12 matches are listed in Tables 1-3. From these data, we can see that the RGB color space is more suitable for our method. When the quantization numbers for color and edge orientation are 128 and 30 respectively, the precision of our method is 65.90%. When the quantization number for color is increased to 6×6×6=216, the performance of our method is reduced, because as the color quantization number is increased, too many noisy features may be obtained, which will not enhance the description power.

Table 1. Average retrieval precision and recall in the RGB color space

RGB color spaces; sub-blocks=2×2; λ=0.5; N=12.										
The quantization number for color	The quantization number for edge orientation									
	Precision (%)					Recall (%)				
	12	18	24	30	36	12	18	24	30	36
216	61.74	62.07	62.29	62.50	62.42	7.41	7.45	7.48	7.50	7.49
128	65.13	65.65	65.74	65.90	65.57	7.82	7.88	7.89	7.91	7.87
64	63.96	64.33	64.63	64.40	63.85	7.68	7.72	7.76	7.73	7.66
32	61.01	61.89	62.22	62.26	61.42	7.32	7.43	7.47	7.47	7.37

Table 2. Average retrieval precision and recall in the HSV color space

HSV color spaces; sub-blocks=2×2; λ=0.5; N=12.										
The quantization number for color	The quantization number for edge orientation									
	Precision (%)					Recall (%)				
	12	18	24	30	36	12	18	24	30	36
192	60.85	60.96	60.83	61.08	61.33	7.30	7.32	7.30	7.33	7.36
128	63.21	63.28	63.35	63.50	63.53	7.59	7.59	7.60	7.62	7.62
108	61.15	61.56	61.64	61.63	61.65	7.34	7.39	7.40	7.40	7.40
72	62.35	62.90	62.68	62.82	62.68	7.48	7.55	7.52	7.54	7.52

Table 3. Average retrieval precision and recall in the L*a*b color space

L*a*b color spaces; sub-blocks=2×2; λ=0.5; N=12;										
The quantization number for color	The quantization number for edge orientation									
	Precision (%)					Recall (%)				
	12	18	24	30	36	12	18	24	30	36
180	58.43	58.89	58.94	59.10	59.14	7.01	7.07	7.07	7.09	7.10
160	55.92	56.99	57.07	57.42	57.22	6.71	6.84	6.85	6.89	6.87
90	53.58	54.74	55.13	55.17	54.65	6.43	6.57	6.62	6.62	6.56
45	52.54	54.29	54.67	54.68	53.89	6.31	6.52	6.56	6.56	6.47

Table 4. Average retrieval precision and recall of different λ and different numbers of sub-blocks

RGB color space; CSA=128; CSB=30; N=12											
number of sub-blocks	Precision (%)										
	λ=0	λ=0.1	λ=0.2	λ=0.3	λ=0.4	λ=0.5	λ=0.6	λ=0.7	λ=0.8	λ=0.9	λ=1
4×4	40.03	54.65	58.49	60.24	61.14	61.93	62.26	62.67	62.58	62.07	61.40
3×3	39.08	56.64	60.92	62.85	63.33	64.01	64.06	64.04	63.93	63.57	63.17
2×2	39.47	61.15	64.83	65.82	65.96	65.90	65.63	65.58	65.19	65.06	65.01
undivided	35.72	60.14	61.89	61.85	61.64	61.26	60.86	60.57	60.36	60.25	60.01
number of sub-blocks	Recall (%)										
	λ=0	λ=0.1	λ=0.2	λ=0.3	λ=0.4	λ=0.5	λ=0.6	λ=0.7	λ=0.8	λ=0.9	λ=1
4×4	4.80	6.56	7.02	7.23	7.34	7.43	7.47	7.52	7.51	7.45	7.37
3×3	4.69	6.80	7.31	7.54	7.60	7.68	7.69	7.69	7.67	7.63	7.58
2×2	4.74	7.34	7.78	7.90	7.92	7.91	7.88	7.87	7.82	7.81	7.80
undivided	4.29	7.22	7.43	7.42	7.40	7.35	7.30	7.27	7.24	7.23	7.20

Table 5. Average retrieval precision and recall of different λ ranged from 0.3 to 0.5

RGB color space; CSA=128; CSB=30; sub-blocks=2×2; N=12											
Performance	Value of parameter in similarity distance										
	λ=0.3	λ=0.32	λ=0.34	λ=0.36	λ=0.38	λ=0.4	λ=0.42	λ=0.44	λ=0.46	λ=0.48	λ=0.5
Precision (%)	65.82	65.60	65.61	65.68	65.90	65.96	66.06	65.78	65.90	65.78	65.90
Recall (%)	7.90	7.87	7.87	7.88	7.91	7.92	7.93	7.89	7.91	7.89	7.91

Table 6. Average retrieval precision and recall of different distance metrics

Performance	Distance or similarity metrics				
	Chi Square	Manhattan	Euclidean	Canberra	Proposed
Precision (%)	53.57	52.14	41.21	64.79	66.06
Recall (%)	6.43	6.26	4.95	7.78	7.93

TABLE 7. THE PRECISION AND RECALL OF EACH NATIONALITY AND THE AVERAGE PRECISION

Category	Precision (%); N=12									
	GLCM	LBPu2(8,1)	LDP(k=3)	Gabor	Hu	HOG	MTH	MSD	CDH	Proposed
Bai nationality	35.33	35.83	31.42	45.67	39.42	41.42	65.83	62.83	58.33	76.67
Jingpo nationality	31.50	38.25	32.42	37.17	27.50	43.67	54.25	42.00	49.17	45.50
Hani nationality	25.58	39.25	37.25	30.83	24.67	46.50	51.17	47.58	49.83	52.83
Miao nationality	42.75	47.83	50.25	45.75	26.67	65.17	60.58	54.08	43.42	80.33
Bouyei nationality	30.92	34.25	34.00	32.25	37.42	22.67	73.17	59.92	61.33	73.50
Va nationality	31.17	38.00	36.92	32.92	24.67	31.75	53.75	57.75	43.42	67.50
Average	32.88	38.90	37.04	37.43	30.06	41.86	59.79	54.03	50.92	66.06
Category	Recall (%); N=12									
	GLCM	LBPu2(8,1)	LDP(k=3)	Gabor	Hu	HOG	MTH	MSD	CDH	Proposed
Bai nationality	4.24	4.30	3.77	5.48	4.73	4.97	7.90	7.54	7.00	9.20
Jingpo nationality	3.78	4.59	3.89	4.46	3.30	5.24	6.51	5.04	5.90	5.46
Hani nationality	3.07	4.71	4.47	3.70	2.96	5.58	6.14	5.71	5.98	6.34
Miao nationality	5.13	5.74	6.03	5.49	3.20	7.82	7.27	6.49	5.21	9.64
Bouyei nationality	3.71	4.11	4.08	3.87	4.49	2.72	8.78	7.19	7.36	8.82
Va nationality	3.74	4.56	4.43	3.95	2.96	3.81	6.45	6.93	5.21	8.10
Average	3.95	4.67	4.45	4.49	3.61	5.02	7.18	6.48	6.11	7.93

4.2. Experiment 2

For analysis the influences of color histogram feature and edge orientation feature on retrieval performance, we experiment with different λ in distance metric. λ is ranged from 0 to 1 by step 0.1. The case of only using edge orientation histogram feature is corresponding to λ=1, and the color histogram feature case is for λ=0. It can be seen from Figure 2 that for most nationalities, the performance rise first and descend latter when λ changes from 0 to 1, which means the effective fusion of both types of feature can improve the retrieval performance. We also find out that for most nationalities, the performance rise sharply first and become gently later, which means color histogram feature play a crucial role in the integrated feature. However, for Jingpo nationality and Hani nationality, the performance rise so gently that they lose to Bai nationality and Bouyei nationality whose performance is worse than them when only using edge orientation histogram feature. This indicates that the color histogram feature seems to have little effect on Jingpo nationality and Hani nationality, because the dominant color of Jingpo nationality and Hani nationality are so similar that they infect each other, pulling down their precision. To test the effect of the number of sub-blocks on retrieval performance, we experiment with different numbers (2×2=4, 3×3=9 and 4×4=16) of sub-blocks and compare them with the undivided case. The results in the Table 4 show that when the number of sub-blocks is 2×2=4, we obtain the highest precision and recall with λ=0.4, and the precision is improved by almost 4 percentage points compared to the undivided situation. When the number of sub-blocks increases, the precision and recall of edge orientation histogram feature increases, but the precision and recall of color histogram feature reduces, and because the color feature is the most important feature of minority costume image, the precision and recall of comprehensive feature reduces.

From Table 4 we can see that the precision and recall when λ=0.3 and λ=0.5 are a little lower than the highest precision and recall when λ=0.4. We continue to experiment with different λ ranged from 0.3 to 0.5 by step 0.02. The results in the Table 5 show that when λ=0.42, we obtain the highest precision 66.06%.

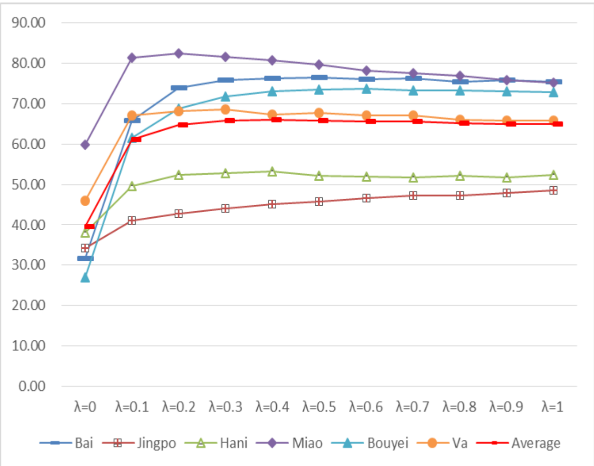

Fig.2. The performance of each nationality with different λ

4.3. Experiment 3

Retrieval accuracy not only depends on strong feature representation, but also on good similarity measures or distance metrics. In order to verify the validity of our improved distance metric with proposed normalization used by our proposed retrieval approach, we investigate the average retrieval precision and recall with different distance metrics when N=12. As seen from Table 6, the proposed distance metric performed better than distance or similarity metrics such as Chi Square distance, Manhattan distance, Euclidean distance and Canberra distance.

4.4. Experiment 4

Comparisons with some conventional methods introduced earlier in this article are conducted in this part of experiments. Table 7 show the performance comparison with other eight methods when N=12. From the results we can see that for most nationalities the proposed method achieves the highest precision and recall, and achieves the best results in the average precision and recall. Because the dominant hues of Jingpo nationality, Hani nationality and Va nationality are all in red and black, their color histogram features are similar and the average precision and recall of them are lower than the other three nationalities. We also find out that our proposed method and HOG all achieved much higher precision and recall of Miao nationality than other method. That is because the edge orientation of Miao nationality costume is prominent.

We continue to experiment on the minority costume image dataset with different number of returned images, as is shown in Figure 3 and Figure 4. We set N ranged from 5 to 100 by step 5. With the number of returned images increased from 5 to 100, the average precision of the proposed algorithm reduces slower than the other algorithms, and the average recall increases faster than the other algorithms, which indicates that our algorithm have good retrieval performance and strong adaptability.

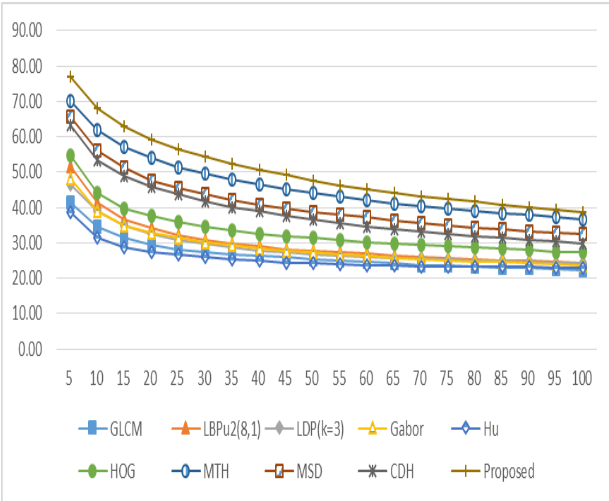

Fig.3. The average precision with different number of returned images

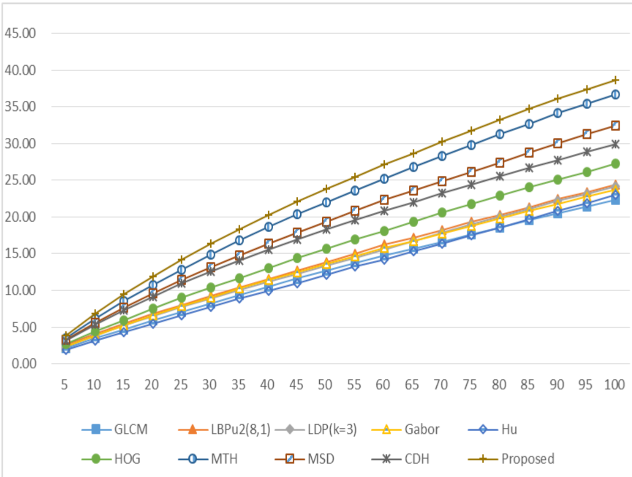

Fig.4. The average recall with different number of returned images

4.5. Experiment 5

In order to use the proposed approach friendly, we design and implement a web-based image retrieval system. This system provide a good user experience, User can use this system to start retrieval by simply clicking the upload button to upload an image in the minority costume image dataset, then the retrieval results will be displayed in another page. Figure 5 shows the retrieval results for the query "Miao nationality" with the proposed approach. The top-left image is the query image, and the similar images returned include the query image itself. One error result is retrieved in the fourth row and first column.

Fig.5. More results for query "Bai nationality"

5. Conclusion and Future work

In this paper, We propose a novel feature extraction approach for minority costume image retrieval, which combines color, texture, shape and spatial features of minority costume image effectively. Our experimental results demonstrate that our method has good retrieval performance and strong adaptability. And it's much more effective than other algorithms reported earlier in the article, such as GLCM, LBP, LDP, Gabor-based feature descriptor, Hu invariant distance, HOG, MTH, MSD and CDH.

Because the local feature of minority costume image are obvious, region-based image retrieval for minority costume image dataset will be studied in future work. Maybe, image segmentation will be considered as an assistant to extract the local feature and semantic feature of minority costume image.

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