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Research on the Second-order Retrieval Algorithm Based on SIFT Feature and Hash Distribution

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Abstract

In this paper, a second-order retrieval algorithm and an improved bag-of-words algorithm were proposed and applied to search similar images. Features of an image were firstly extracted by the method of SIFT. The word frequent table of the features was then created by the improved bag-of-words algorithm which is a combination of hash algorithm and K-Means algorithm. Based on the word frequent table, similar images were finally identified by the second-order retrieval algorithm. However, the second-order retrieval algorithm includes two steps. The first-order retrieval is a cursory search and it pays much attention to the similarities between the distributions of features, the second-order retrieval is an accurate search and it depends on the proportion of the same feature points to the total points. The experiment results imply that this method has good performance on the aspect of recall, showing high accuracy and efficiency.

Keywords: *SIFT features; image retrieval; bag of word algorithm; feature word frequent table; second-order retrieval*

1. Introduction

With the high-speed development of big data, more and more attention have been paid to the widely usage of image retrieval technology. The conventional way of searching similar images is mainly depending on the text description from manual analysis. However, the major limitation of the approach is that once the number of images exceed a certain magnitude, the labor cost will rise immediately. In addition, if the searching target changes from text to image, this approach will be difficult to meet new requirements. Thus, the traditional searching method cannot adapt to the changing situation, consequently calling for technology upgrade. Fortunately, owe to the development of computer vision, the feature-based image retrieval technology is capable of fully satisfy the requirements. [1].

In order to realize image recognition, image features need to be extracted at first. The traditional feature extraction approach mainly includes texture edge feature extraction and color and gray level statistical feature extraction. Seetharaman[2] proposed a method called CBIR (Content Based Image Retrieval). The multi-resolution based CBIR consists of texture and colors features. The method extracts HSV (Hue, Saturation, Value) color feature and HSV texture feature of an image by calculating a co-occurrence matrix, and then the feature vector can be formed by the two extracted features. The experiment results showed that the

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proposed CBIR has obvious advantages, as compared with the traditional way of using a gray-level co-occurrence matrix.

However, this method also has the shortcoming that only the color and texture features of HSV were extracted. Therefore, a new method which is based on the description of structuring element was proposed by Wang X [3]. In the method, structuring element descriptors are used to describe the image texture. Meanwhile, it derives structuring element histogram from the statistics of the descriptors, within 72 kinds of color layers expressed in the image HSV. This histogram is able to describe the image more easily because of the integration of texture and color features. Their results indicated that this method has a good retrieval performance.

Although satisfactory results can be achieved by the above ways which use texture and color features to describe images, but the effect still needs to be improved when deformation or different lights shining exists.

In recent years, SIFT features are widely used as a partial feature descriptor to retrieve images. It is mainly because the SIFT features can be invariant to image scaling, rotation and illumination changes, Montazer G A [4] provides an approach that SIFT clustering method is applied in image retrieval. Two ways were adopted to solve the problem of large memory and long-time used during the SIFT features extraction. The first one is to reduce the scale of the cluster, only 16 feature clusters extracted, and changing the scale from k*128 dimensional matrix to 8*16 dimensional matrix; the second one is reducing the size of feature matrix to 1*18 in the eight directions of SIFT feature. This approach optimizes the process of SIFT feature extraction and it also shows high accuracy in image retrieval.

However, Montazer G A [4] improved the work efficiency by enhancing the SIFT feature extraction, but there has been no significant breakthrough in his retrieval algorithm. Moreover, the traditional Euclidean matching is inefficient. Therefore, in order to achieve image retrieval with high efficiency and great accuracy, a novel approach for second-order retrieval algorithm is proposed in this paper. This method is based on the SIFT algorithm and the K-Means algorithm, which are used to extract image features and to establish word frequency table respectively. Our proposed method has better performance compare with the traditional bag of words algorithm and Euclidean matching method.

2. Extracting features and creating word frequent table

2.1. Extracting and clustering features

The first step of creating the word frequent table is to extract the image features. SIFT is the mainstream method to extract image features. It has a very good robustness to the influence of light and deformation. SIFT is able to remain scale-invariant when facing the scaling, rotation and even affine transformation. So, this paper uses SIFT to extract image features.

During the image processing, the type of features that are extracted by SIFT is various. In order to be matched effectively, finding out a good way to extract feature word is in needed. Clustering is applied in many methods. It is an unsupervised classification approach, and it can gradually reduce the error of the objective function through iterative calculating on the SIFT features. The final clustering results will be obtained when the value of the objective function is convergence. Compared with other clustering algorithms, K-Means has the advantages of average stability, good effect of spectral clustering, less time of hierarchical clustering and so on. The goal of the algorithm is to find out a number of K center points c1,c2,…,ck so that the sum of distance squares between each object xi and its nearest centroid cv can be minimized [6]. The process of K-Means clustering algorithm is as follows:

1) Selecting K objects (c1,c2,…,ck) randomly as centroids;
2) Calculating the distance between each centroid and object xi, then classify the object to the nearest category of centroid;
3) Recalculating the centroid of each category that has been obtained again;
4) Iterative calculating on step 2) ~ 3) until the new centroid is equal to the original one or their distance is less than the given threshold. If the distance satisfied these conditions, the algorithm terminates.

The terminal condition of the algorithm can be expressed as follow:

$$D=\sum_{i=1}^{n} \min_{r=1\ldots k} (x_i - c_r)^2 \tag{1}$$

If the value D is a convergence result, the algorithm terminates; otherwise, return to step 2).

2.2. Creating word frequent table

The word frequent table is the key factor for image retrieval. In this paper, the word frequent table is created depending on bag of word algorithm. The algorithm will cluster the partial feature of image into feature word. The distribution of the feature word can be expressed in a statistical histogram. And the image will be expressed as a statistic vector of frequent word [7]-[8] depending on the statistical histogram. All of the SIFT features of each image will be classified into word frequent table. The word frequent table records the frequent statistics that features of each image distributed on thecategory of each visual word(clustering result of SIFT features).

From the section 1.1, we know that all of the SIFT feature sets V = {v1, v2, …vn } can be clustered into several feature words K = {k1, k2, …km } by the unsupervised method K-Means. Then all the partial features of image can be projected onto these feature words [9], and the histogram statistics can be formed by the frequent of projection. finally, the word frequent table and vector expression of the image can be established by the histogram statistics.

The traditional bag of word algorithm will classify the feature points into the nearest visual word depending on the Euclidean distance. But when the number of visual feature words are too many, all of the feature points need to be calculated the Euclidean distance one by one, and this will lead to the decrease of the efficiency. So this paper made some improvements to the bag of word algorithm: set a Hash function as H(x) which is refer to the 128 dimensional vector of SIFT feature point.

$$H(x)=\sqrt{\sum_{i=0}^{128} x_i^2 / r} \tag{2}$$

The letter r is a given coefficient. All of the m feature words will be distributed into t classes after the Hash calculating, and each class followed by many feature words. As shown in Figure 1, when we do the projection calculation in the image, the first step is to do the hash calculation and find the corresponding class ti of the feature point v. Then find out the corresponding visual word by calculating the Euclidean distance between feature point v and each visual word kij in class ti. Thereby the amount of calculation will be greatly reduced.

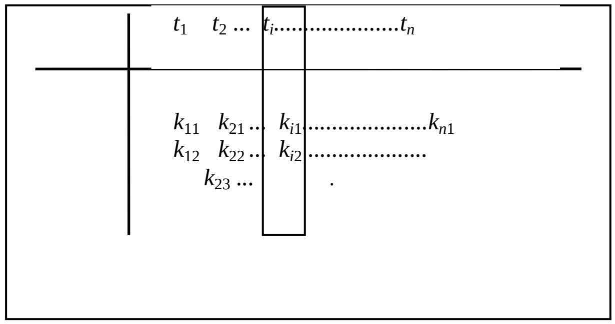


Figure 1. Feature points mapping

Example: supposed that there are 1 million feature points in the image and all of them need to be clustered into 10000 visual words. If the normal bag of word algorithm is used to calculate the word frequent distribution in the image, the number of Euclidean distance calculation may be 10 billion times. But if we use the improved method, the calculation times may reduce to 101million. The reason is assuming that the 10,000 visual words will be divided into 100 categories by the Hash calculation and each category will have 100 visual words rightly. Thus the amount of visual words, that need to do the Euclidean distance calculation, have reduced from the original 10,000 to the current 100. It means that the sum of the calculation times only contains 1 million times of Hash calculation and 1 billion times of Euclidean distance calculation. That is why the speed of calculating the distribution of word frequent is greatly improved.

As shown in figure 2, the word frequent table records the number and the corresponding proportion of feature points that each image has projected on the category of visual word ki. This word frequent table contains all the feature point distribution information of images that stored in the database and it can greatly help improve the efficient of image retrieval afterwards.

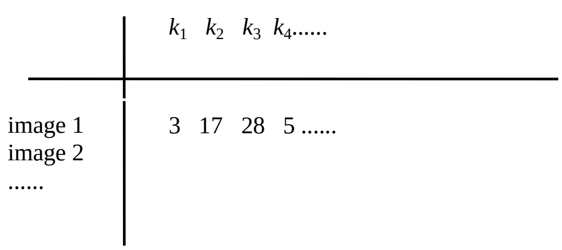


Figure 2. Sample frequency

3. Algorithm implementation

3.1. Traditional matching algorithm of using Euclidean distance

The performance of image retrieval algorithm determines the efficient and effective of searching. Traditional retrieval methods set the Euclidean distance between two images as the similarity criterion. Assuming that there are two images P and Q, and the SIFT feature point set of the image P is V = {v1, v2, …vn }, the SIFT feature point set of the image Q is W= {w1, w2, …wm }, and the letter m, n represents the number of feature points in image P and Q respectively. When we judge whether it is similar between image P and Q, the first step is to find the corresponding feature point-pairs in these two images. The KD tree (k-dimensional tree is a kind of data structure that can be used to divide K dimensional data space) can be used to create index for all feature points. Then using the BBF (best bin first) algorithm to find the nearest neighbor and next-nearest neighbor of the feature vector. Therefore, a KD-tree should be created for the feature set V of image P at first, then searching the nearest neighbor and next-nearest neighbor of the feature point wj in set V. Suppose d1 is the nearest neighbor of point (wj, V), d2 is the next-nearest neighbor of point (wj, V), letter r is a given proportion threshold. The comparison result between proportion threshold r and d1 /d2 can determine whether the point wj will find the matching feature points vi in set V. And the distance calculating function, that basing on SIFT feature, can be expressed as follow:

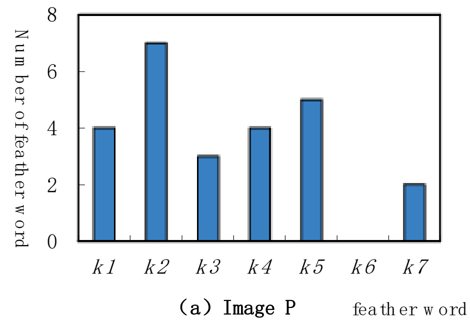
$$d=\sqrt{\sum_{t=0}^{z}(v_{i_t}-w_{j_t})^2} \tag{3}$$

Letter t is the sequence number of the corresponding feature point-pairs and letter z represents the total number of the pairs. However, this method does the image retrival by calculating the similarity between two images, and its efficient is unsatisfactory. When the size of the image database reaches a certain magnitude, the number of feature points will become very large either. The calculation of matching on such a huge number of features is enormous which is almost impossible to do. Therefore, this paper proposes the second-order retrieval algorithm for image searching which has a fast and efficient performance.

3.2. The second-order retrieval algorithm

The second-order retrieval algorithm is divided into two parts, first-order retrieval and second-order retrieval. The first-order retrieval is a coarse searching, and its main task is to filter a part of images for the second-order retrieval. Its retrieval mainly depending on judging whether the distribution of image feature point is similar.

Figure 3 is the distribution of the 7 feature words which are clustered from the two images P and Q. When the structure of the feature distributions are more similar, the two images are more similar too.



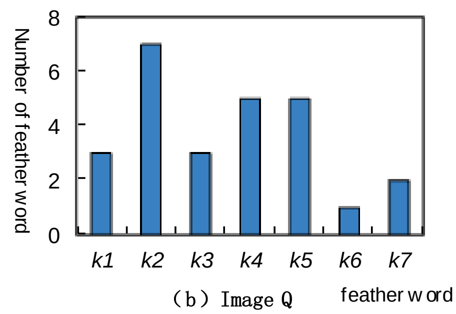


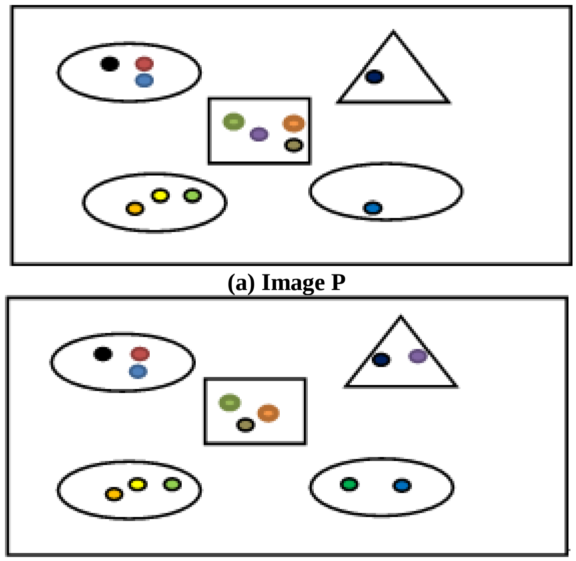
Figure 3. Comparison of characteristic distribution for P、Q

The proportion data (Data in the word frequent table)of image feature distribution that obtained in part 1.2 are stored in the .data file. By calculating the Euclidean distance between their proportion data, we can judge whether it is similar between different distributions can rely on . The formula can be expressed as follow:

$$d=\sqrt{\sum_{i=0}^{k}(p_i - q_i)^2} \tag{4}$$

In the formula, pi represents the proportion that image P has occupied in the category i, qi represents the proportion that image Q has occupied in the category i. Result d represents the reference value of similar. The smaller the d, the more similar the two images are.

After the filtering of the first-order retrieval, the selected images will be searched by the second-order retrieval again. The second-order retrieval introduces the judging of direction which will judge whether the corresponding feature point-pairs is belonging to the same feature word. The corresponding feature points of the two images may project onto different feature word. As shown in Figure 4, points with the same color are the corresponding feature points. The more corresponding feature point-pairs fallen on the same feature word, the more similar that the two images are. After this step, we can select out those images that are much more similar than before.



(a) Image P

(b)Image Q

Figure 4. The example for feature points that belong same class

The method of searching the corresponding feature points have been analyzed in the section 2.1. SIFT feature points of image P have been extracted as set V = {v1,v2, …,vn }, and SIFT feature points of image Q have been extracted as set W= {w1, w2, …,wm }. In section 1.2, each feature point of the image needs to be marked out when the word frequent table will be established. In other words, we need to mark out which category of the table is the feature point belonging to. Each feature point of the image is a kind of structure data, and a data item k can be added into it. This item will be used to identify the category that the feature point vi belongs to. During the image matching, the corresponding feature point-pairs vi and wj will fall on the same feature word if their item k equals to each other. Vector a={a1, a2, …, ak} is used to store the number of feature points that have fallen on each category. The initial value of the vector a need to be set as 0, and it is calculated as follow:

$$a_i = \begin{Bmatrix} a_i + 1, v_i = w_j \ \& \ k = 1 \\ a_i, other \end{Bmatrix} \tag{5}$$

The similarity formula that using in the second-order retrieval:

$$d = \sum_{i=0}^{k} \left(\left(a_i \left(\frac{t_i}{n} \right) \right) / N \right) \tag{6}$$

In the formula, ai represents the number of feature points that the given image and the selected images all have fallen on the same category i ; n represents the total feature points of the selected images; ti represents the number of feature points that the selected images have fallen on the category i ; ti/n represents the word frequency that the selected images fall on the category i ; ai (ti/n) represents the number of feature points according to result of the weight distribution calculating; N represents the total number of feature points that the selected image has; after divided by N, the result represents a weight proportion that the number of corresponding feature points, which have fallen on the same feature word, divided by the total number of feature points. Since different images have difference on the total number of feature points, it will be much more accurate to use the proportion to judge whether the two images are similar.

4. Experiment

4.1. Experimental environment

This retrieval system has developed in window8.1 operating system; the version of Visual Studio is VS2010; image library, which used in the experiment, contains 10000 cultural relic images. These images will be used to test whether the new retrieval algorithm can match the similar images from the image database or not. Some of the example images are shown in figure 5 and figure 6.

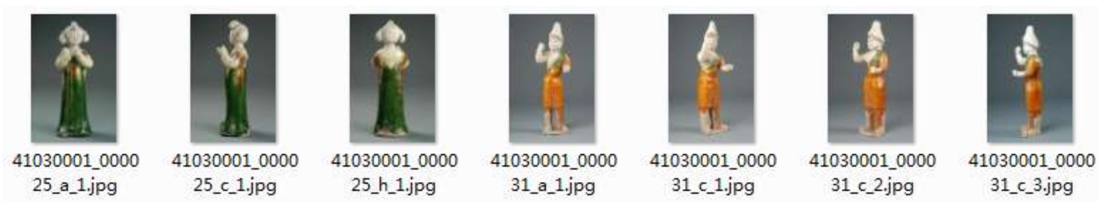


Figure 5. Cultural relic image feature sign before and after comparison : Original images without features

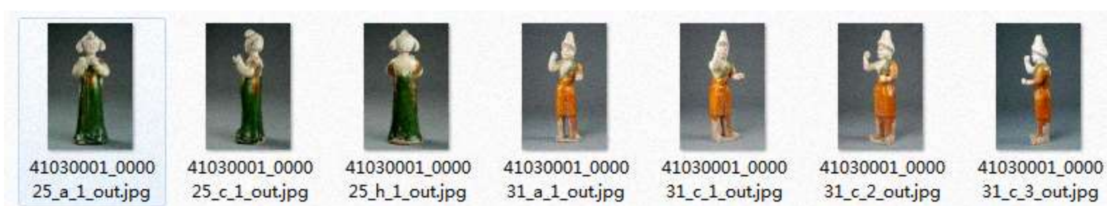


Figure 6. Cultural relic image feature sign before and after comparison : Images with features

4.2. Experimental result and analysis

During the image retrieving, one of the difficult works is to find the corresponding feature point-pairs. Suppose v is a feature point of image P, and now we want to find the corresponding feature point in image Q. The first task is to find the two nearest neighbor points in the image Q. If the proportion that nearest neighbor distance divided by the next-nearest neighbor distance is less than value r, the two points can be recognized as a corresponding feature point-pairs. Therefore, the proportion threshold value r is very important factor. It determines the number of corresponding feature point-pairs that can be found and it can also influence the result of the experiment.

The suitable value r will be decided by a set of experiments. Firstly, a set of 1000 images are selected as the experiment data, then took out 30 images to do retrieve for 30 times, and the value r will be determined by the results of the searching. The experiment results are shown in figure 7.

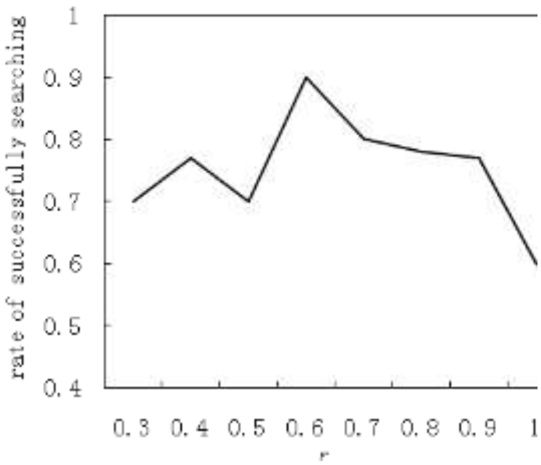
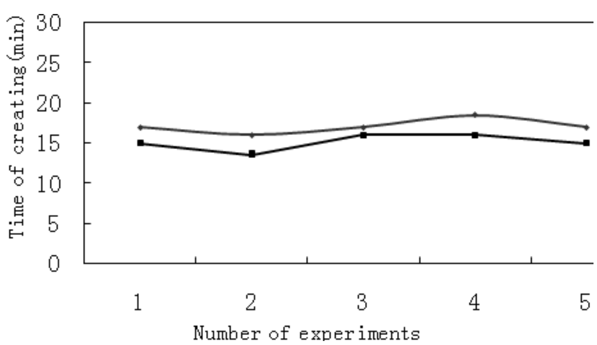


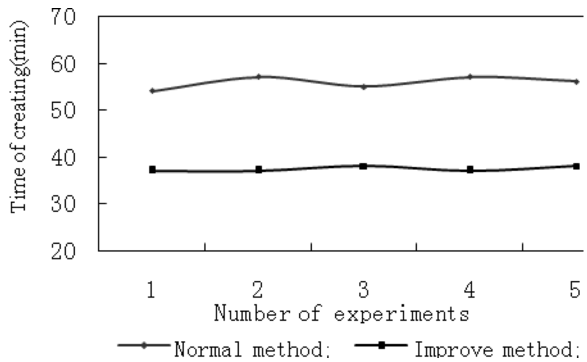
Figure 7. The influence of retrieval in different r

In Figure 6, it can be found that when r locates in the vicinity of 0.6, the rate of successfully searching reached the highest value. It also means when the value r equals to 0.6, the effect and performance of the retrieval is the best. Thus, the r will be given a value of 0.6 in the following experiment.

In order to verify the effect of using improved bag of words algorithm to create word frequent table, 10 experiments have been done to compare the different effectiveness between the improved bag of word algorithm and normal method respectively. The first 5 experiments are based on 1000 cultural relic images, and the last 5 experiments are based on 10000 cultural relic images. The results of the experiments are shown in Figure 8:



(a)1000 cultural relic images



(b)10000 cultural relic images

Figure 8. Contrast experiment for word frequency table construction

The experiment results above show that the improved algorithm can obviously reduce the time of creating the word frequent table. Meanwhile, another conclusion, which can be drawn from the comparison results, is that the effectiveness improved is not obvious when the number of the experiment data is few ,but if the amount of the experiment data is large, the effect improved will be obviously either. This is because the improved method reduces the time of calculating the Euclidean distance that between the feature points and the visual words, but it also increases the time of Hash calculating for the feature points. When the number of image is few, the number of visual words is also few, the time for hash calculating will occupy a relatively large proportion of the whole time. Thus the effect improved not obviously. But the proportion of the time for hash calculating will become smaller when the number of visual words become a bit larger, and then the effect of reducing time will be much more obviously.

This paper uses the Normal Recall (NR) [10] to evaluate the performance of this system. Suppose N represents the sum of images; T represents the number of relevant images which is inside the N; ns represents the sequence number which is sorted by similarity degree. R represents the number of real similar images in the database.

According to the retrieval results, the average ranking of the relevant images can be expressed as:

$$A=\frac{1}{\mathrm{T}}\sum_{s=0}^{T} n_s \tag{7}$$

The ideal average ranking of relevant images can be expressed as:

$$L=\frac{1}{\mathrm{R}}\sum_{n=0}^{R-1} n \tag{8}$$

The formula A/ L represents the Normal Recall. When the value of A/ L become much closer to 1, the effect of retrieval will be much better.

A number of 250 cultural relic images, which come from 25 categories, will be chosen and each category contains about 10 similar images inside. Thus, the ideal average ranking of relevant images is 4.5. From the experiment result of the wood searching in Figure 9, we know that the relevant image sequence is 1, 2, 3, 5, 6, 7, 9, and the value of average ranking is (1+2+3+5+6+7+9)/ 7=4.71.

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Figure 9. The second retrieved result of wood carving

Table 1 shows the NR test results about 7 categories; figure 10 shows the comparison of the two methods in the aspect of NR; Table 2 shows the comparison of the two methods in the aspect of retrieval time.

Table 1. The recall of two methods

Method	Recall *A*/*L*						
	Bronze	Procelain	Wood Carving	Stone Tablet	Painting and Calligraphy	Facial Makeup	Hook Halberd
Euclidean distance	0.89	1.30	1.00	1.11	1.26	1.18	1.20
The second-order retrieval	1.04	1.19	1.08	1.11	1.04	1.21	1.11

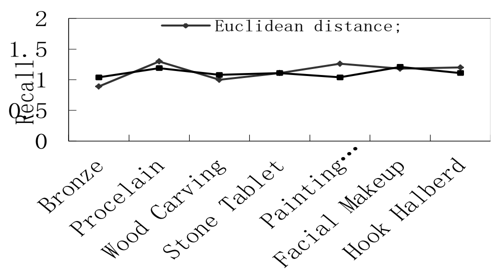

Figure 10. Comparison of two methods of recall

Table 2. Query time compare of two method

Method	Time *t*/s						
	Bronze	Procelain	Wood Carving	Stone Tablet	Painting and Calligraphy	Facial Makeup	Hook Halberd
Euclidean distance	0.060	0.292	0.411	0.092	0.140	0.430	0.229

The second-order retrieval	0.052	0.186	0.300	0.081	0.137	0.242	0.120

From the experiment results, we can know that when it is compared to the method of normal Euclidean distance calculating, the second-order retrieval algorithm can reduce the retrieval time, improve the efficient of searching and do not decrease the NR . However, the SIFT algorithm is more suitable for searching images with prominent texture features. And if it is difficult to get the information of image gradient changing, the retrieval effect will be unsatisfactory.

5. Conclusions

In this paper, the second-order retrieval algorithm is proposed basing on the image SIFT features and it has a innovation in the mode of searching, and it also has a higher efficiency and accuracy than the normal approach. Improved bag of words algorithm can speed up the process of creating word frequent table; the second-order retrieval algorithm can find out the similar images much more quickly and accurately.

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