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Research and Application of a Combined Art Image Query Method

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Abstract

With the development of society, number of art image becomes bigger and bigger. In order to classify the art images, it is necessary to retrieve the images with common features. Different from the commonly used image query method, art images are always seen by specific researchers and to study and classification, and it is much more important for the query method with high retrieval precision. So it is important to develop a better query method specifically used for the art image query. The main work of this paper is to establish a combined method to improve the art image query precision without decreasing the query time seriously. The combined query method includes several steps: (1) Initial query. The tag query method and the semantic query method will be used. The initial query results includes the results searched by both the methods. (2) Reorganization of the initial query results. The repeated images will be cleared and only one image will be left. (3) Distance based results rechecked. The most relative image will be ranked in front of the list and the less correlation image will be cleared. (4) Reordering the images. All the images will be reordered by the distance which reflects the correlation of the query image. According to the experimental verification, the combined method can improve the query precision.

Keywords: *art image, combined method, image reordering, query precision, query time*

1. Introduction

With the development of Internet and multimedia technology, the explosive growth of multimedia information [1-3] is presented. Facing to the database with a massive image, people can quickly and accurately obtain similar images only by effective image retrieving [4-8]. Comparatively, although the number is smaller than that of Internet multimedia pictures, the art image [9-11] contains a large amount of information, meanwhile, some artistic images may be contained in other images. Therefore, image search [12-14] with accurate results can help to the image classification and analysis. How to quickly get the search results with guaranteed high query accuracy is quite important.

The traditional method of image query is based on the image number and label. Specifically, indexes, including texts, number tags, contained some information described is added to the images. When searching the image [15], the text and number tags will be retrieved. And then, the image search becomes the exploration based on index. Because the image is rich in content, it is difficult to completely express only with a text label. Therefore, there are often mistakes in the query process. In addition, if the standards for the description change, the label is also reproduced to meet the requirements of the new query. Especially, these text labels are selected and added up to the image by observer, and it will be greatly affected by the subjective factors. This is because different observers or the same observer under different conditions may give a different description with a

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pair of images. The results will be bot objective. Due to the no uniform standard, the text may be contradictory. How to effectively analyze the correlation of user's retrieval intention and give a better solution to the current semantic gap of the image will be quite important to improve the retrieval performance of the image retrieval system.

The image query can be divided into two steps as follows: Firstly, search the images according to the semantics [16-17]; secondly, the results of the semantic query should be sorted [18-19]. So far, there are two aspects of image retrieval in the image search process. One is the correlation between the retrieval results and target image [20-21], and the other one is the diversity of the results compared to the target image [22-23]. The correlation of the retrieval results is whether the images shown in front of the results list are related to the user's retrieval intention. The reordering method based on the correlation is called correlation reordering method. There are usually two basic assumptions used in the method:

(1) Each pair of visually similar images should have relatively close relevance scores, so position of them in the reordering list should also be relatively close;

(2) Despite of noise, the initial retrieval results can give some image correlation information to some certain extent.

Therefore, if reordering the initial search results, the reordering results should draw lessons from the initial results. According to correlation analysis of querying, consistency of position of the related images should be provided before and after the reordering process.

It is different from the correlation reordering, diversity based retrieval results pay more attention to the image diversity of results returned. That is to say that good retrieval results should include all visual pattern image [24-25] and without missing images in the results list. With different weight, image diversity of reordering should provide as much information to the user and avoid visual redundancy problem in image retrieval process.

It is difficult to propose a best reordering method for the art image results. The main work of this paper is to establish a combined method to improve the art image query precision. The aim of the method is to put the most relative image in front of the results list and meet the demand of the query. The remainder of the paper is shown as the following: some typical reordering methods are introduced in Section 2; the new combined method is described in Section 3; the verification for the new method is shown in Section 4; and the Conclusion is shown in Section 5.

2. Typical Reordering Methods

So far, the image reordering method is mainly according to image low-level visual features, such as color moments, edge histogram, and bow histogram. The image correlation information will be searched and the reordering work will be processed. These methods are mainly from the low level visual features of the image, and these methods can be classified into the following categories:

(1) Clustering based method. This method assumes that the images in the retrieval results meet the query demand are similar to each other, and images with no correlation are visually different. According to the cluster methods, noise images with no correlation to the query demand will be classified into sparse and discrete clusters, and the noise images will be filtered out according to a specific method.

(2) Classification based method. This method regards the initial retrieve images at two kinds of correlation and no correlation. Therefore, the image reordering problem will be transformed into the image classification process.

(3) Learning based method. This kind of method, combined with statistical machine learning theory, is used to analyze the user's search intention according to the reordering of the initial image retrieval results, and the scheduling model which can reflect the search characteristics will be positively learned. Then, the aim of the image reordering will be realized.

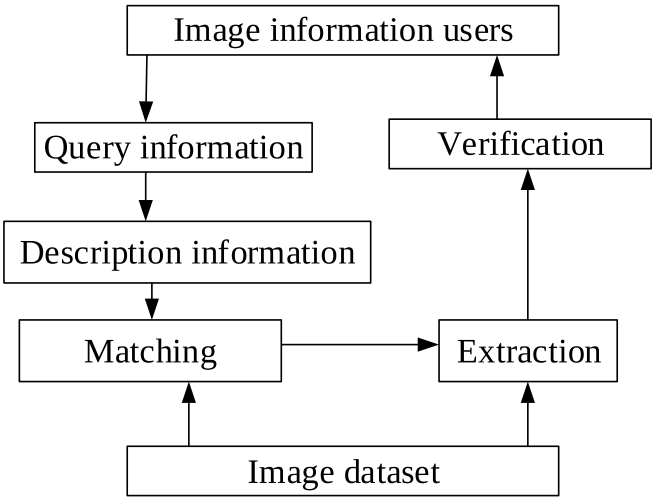

Figure 1. Flow Chart of the Template Matching

So far, there are two main ways for image retrieval. One is the text based query method, and the other one is the image based query method. For both methods, different retrieval results correspond to different reordering structures, and information contained in each query sample is different. Therefore, single ranking model is unable to all query samples with high efficiency. Although learning based method can learn corresponding ranking function adaptively according to the query characteristic, it is often unbearable for the expense of online training. At the same time, the training model often has poor expansibility due to the limited training samples of offline trained learning. So, over fitting problem is often difficult to avoid when the offline method is used.

On the other hand, the image reordering problem can be considered as a process of noise data filtering, and the similarity measurement between images is inevitable. However, because of the existing semantic gap between the low-level visual features and high-level semantic concepts of the image, images with similar visual features do not necessarily mean similar semantic concepts. Then, the final retrieval results are often unable to well match the user's search intention.

3. The Combined Search Method

Since the disadvantage of the existing methods, it is quite important to develop a new search method combined with the visual feature and the semantic concepts. For the article image, the retrieval speed is not very important, instead, the retrieval results are quite important. Here, a combined method with semantic retrieval and results filtration has been proposed to improve the results quality.

3.1. Semantic Retrieval

The image set can be described as:

$$T = \{I_1, I_2, ...I_n\} \tag{1}$$

Then, the feature of Dense SIFT local feature points based visual word bag is extracted from each image:

$$V^i = \{p^{(i)}(v_1), p^{(i)}(v_2), ..., p^{(i)}(v_k)\} \tag{2}$$

Assumption that probability distribution of semantic attributes can be obtained by the semantic attribute of the image, then

$$V^i = \left\{p^{(i)}(a_1), p^{(i)}(a_2),..., p^{(i)}(a_m)\right\} \tag{3}$$

Here, a_j and v_j mean visual word and semantic attribute. The relation between visual word and semantic attribute can be described as $p(v_j \mid a_k)$. Then, the mapping dictionary between the visual word and the semantic attribute is composed of the transfer probability of visual word and semantic attribute.

Taking the sigmoid function into the method:

$$f(x) = \frac{1}{e^{-x}+1} \tag{4}$$

The semantic attribute of the image is mapped by sigmoid function, and the prediction fraction of each semantic concept is mapped to the probability distribution of 0~1 range. If we use A' as the semantic attribute of the image without mapping, the probability distribution of the semantic attribute can be expressed as:

$$A = f(A') \tag{5}$$

Here, f is a sigmoid function.

The purpose of visual semantic mapping dictionary learning is to estimate the transfer probability $p(v_j \mid a_k)$. According to the Bayesian total probability formula, the probability can be described as:

$$p(v_j) = \sum\nolimits_i p(v_i \mid a_i) * p(a_i) \tag{6}$$

The objective function of reconstruct learning can be described as:

$$\begin{aligned} &\min{}_D \frac{1}{2}\left\| B_{d\times k} - D_{d\times n} A_{n\times k} \right\|_2 \\ &s.t. \sum\nolimits_i D_{i,j}^2 \le 1, \forall 1,2,...,n \end{aligned} \tag{7}$$

Where, B is the visual word distribution matrix; D is the visual semantic mapping dictionary; A is semantic attribute probability distribution matrix.

From the perspective of dictionary learning, the probability of a visual word in a picture can be expressed approximately by a linear combination of the probability of each semantic attribute of the image. The visual semantic map dictionary can be regarded as a group of the basics while the semantic attribute probability distribution is the coordinate of the corresponding basic. The reconstruction problem of the dictionary is actually the problem of solving corresponding basic with known coordinate.

3.2 Distance Matching Method

Here, invert list technology is taken into the method. For the query image features, after the retrieval of recent w inverted list, the overall filtration will be used for the results to filter the feature points. The feature points around the query feature point will be reordered. The key to the method is to determine a proper radius. A sphere with the query feature point at the center will be constructed. The sphere will be used to filter the feature points locates outside it. The results in the sphere will be reordered in this step.

Give an inverted index structure $L = \{l_1, l_2,..., l_k\}$, and the corresponding clustering centers are $C = \{c_1, c_2,..., c_k\}$. The detailed query process can be divided into the following steps:

Step1: Calculate the Euclidean distance $d = \{d_1, d_2, ..., d_k\}$ for all clustering centers in q and D.

Tep2: Takes the smaller distance from $\{d_{q,1}, d_{q,2}, ..., d_{q,w}\}$, and the all the feature points in the invert list are the query results $RS_q = \{y_1, y_2, ..., y_m\}$

Step3: Construct a sphere with Q as the center. Radius Rq of the sphere can be determined according to the distance $d_{q,i}$:

$$Rq = \lambda \times \frac{1}{w} \sum_{i=1}^{w} d_{q,i} \tag{8}$$

Where, λ is the ratio coefficient, which is used to adjust the radius of the sphere. The purpose is to get the minimum radius of the query accuracy to filter out the similar results as much as possible.

Step4: Calculate the distance $d(q, y_i)$ between query characteristics q and RS_q characteristics, and only results meet a specific condition will be retained. The specific condition can be described as:

$$d(q, y_i) = \|q - y_i\| \leq R_q \qquad i = 1,2,...,m \tag{9}$$

Step5: According to the distance between features in RSqnew and query features, the feature points with the minimum distance will be selected as the final results.

Among them, step 3 and step 4 are the concrete steps of the comprehensive filtering. The other steps are the same as the traditional inverted index based retrieval method and the residual based retrieval method. Comprehensive filtering didn't change the construction types of the inverted index structure, and the only difference is the addition of the filtration of the query results in the feature search process. Thus, for the inverted index structure $L = \{l_1, l_2, ..., l_k\}$, the insertion process of the image feature x into the index structure is similar to that in the commonly used inverted index structure.

3.3. The Combined Query Method

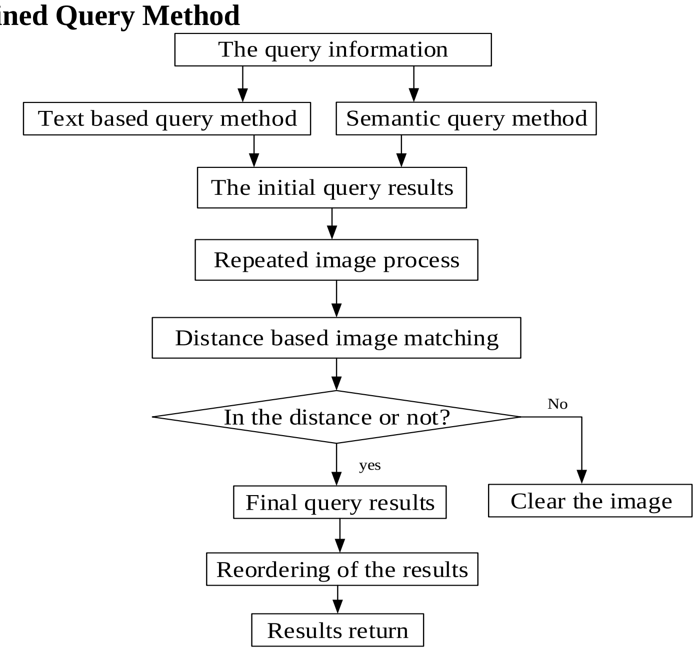

Figure 2. Flow Chart of the Template Matching

The combined query method includes several steps: (1) Initial query. In this step, the tag query method and the semantic query method will be used. The initial query results include the results searched by both the methods. (2) Reoganization of the initial query results. In this step, the repeated image will be cleared and only one image will be left. (3) Distance based results rechecked. The most relative image will be ranked in front of the list and the less correlation image will be cleared. (4) Reordering the images. All the images will be reordered by the distance which reflects the correlation of the query image. The flow chart of the combined query method can be shown in Figure.2.

4. Verification

In order to verify the query precision improvement of the proposed method under the premise of without much affecting the query speed, some experiments are designed. Here, the new proposed method is used to compare with residual quantized based retrieval method. Query adaptive filtering method has also been discussed. This paper is to test and evaluate the retrieval performance of the new algorithm in the open SIFT feature dataset [26]. Specific information of the data set is shown in Table 1and the results is compared with that in reference [27]. All the experiments are operated on a computer with Intel Core I5 with the frequency of 2.8GHz and 4G memory. The software is matlab R2011b.

Table 1. Information in the Dataset SIFT

Dataset	sift
Feature dimension	128
Training set	100000
Dataset	1000000
Query set	10000

The Figure.3 to Figure.5 give query precision with the combined method and the reference method when the parameter k is 64, 256 and 1024. And Figure.6 to Figure.8 give the query time of the combined method and the reference method. Where, R is the number of the query results and its value is 100. Parameters of k and w are the inverted list number of the index structure and the number of inverted permutation table. The experiments will prove the proposed new query results method can improve the query precision without seriously decrease the query speed.

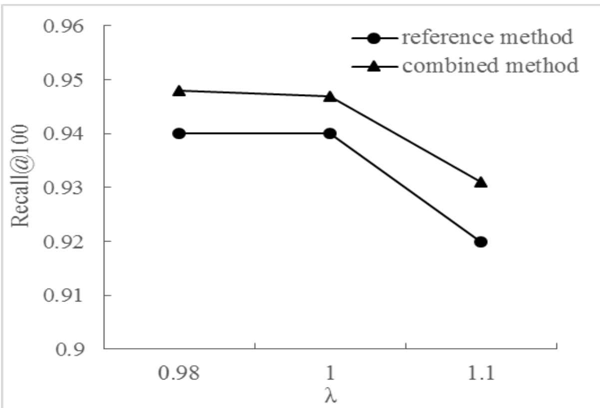

Figure 3. The Query Precision with λ When K=64/W=8

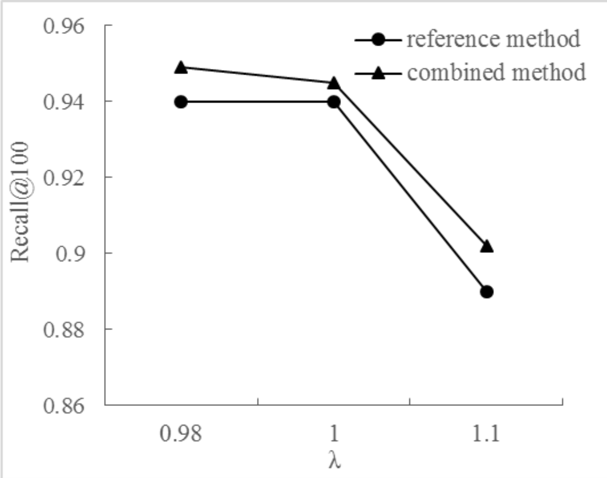

Figure 4. The Query Precision with λ When K=256/W=16

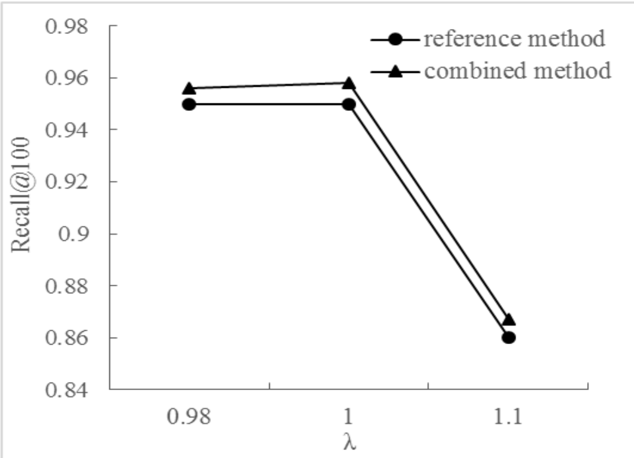

Figure 5. The Query Precision with λ when K=1024/W=32

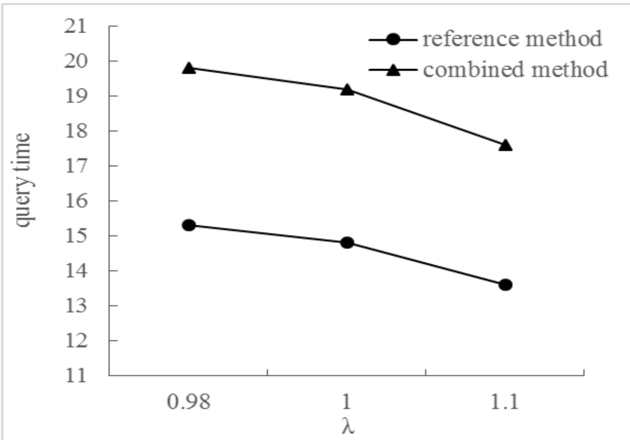

Figure 6. The Query Time with λ when K=64/W=8

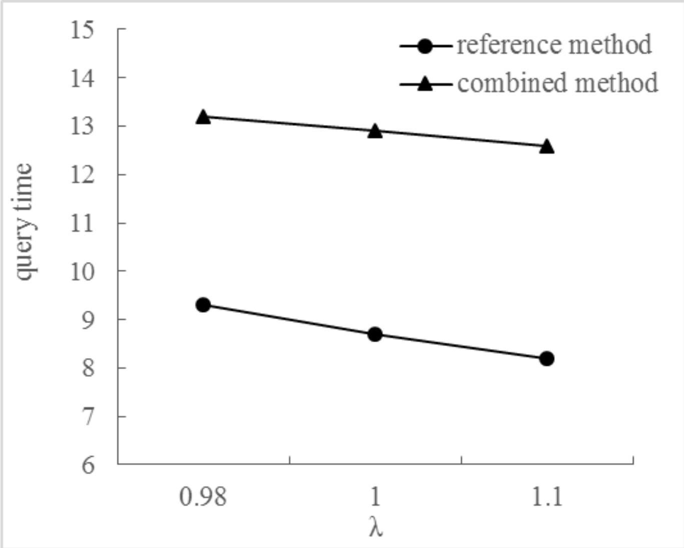

Figure 7. The Query Time with λ when K=256/W=16

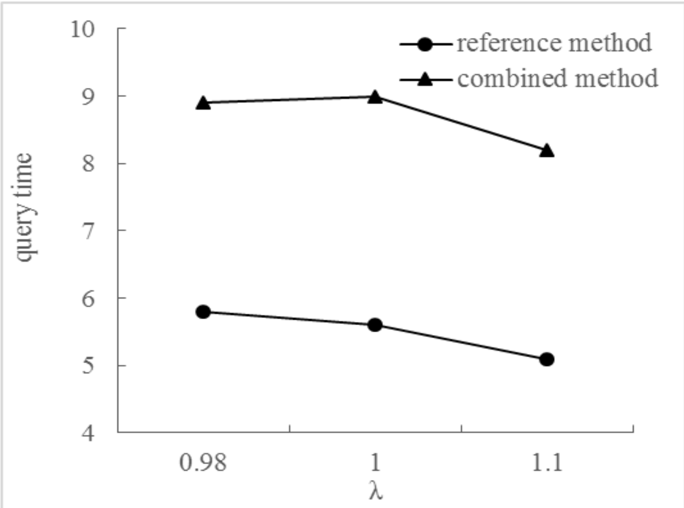

Figure 8. The Query Time with λ when K=1024/W=32

From Figure.3 to Figure.5, it can be seen that the combined method can improve the query precision. In fact, due to the combined method add a step in the query process, the number of initial results will be increased. This is due to the addition of the images with less correlation. When the initial image results number is increased, the query precision is increased. At the same time, due to the addition of the query step, the query speed becomes slow. For long search time, the increasing time is relatively short, but it is relatively long when the search time is short. Therefore, how to reduce the search time in the short-time-query process is important. It is also can be seen that when the λ is optimized, the value of it is also slightly affected by the k and w.

5. Conclusion

With the development of society, number of art image becomes bigger and bigger. In order to classify the art images, it is necessary to retrieval the images with common features. Due to its own characteristics, art images query method much more important with high retrieve precision. The traditional method of image query is based on the image number and label. Specifically, indexes, including texts, number tags, contained some information described is added to the images. Due to the rich content, it is difficult to completely express only with a text label. Thus, there are often mistakes in the query process. The image query can be divided into two steps as follows: search the images and sorted. Both of the two steps are quite important.

In the paper, a combined method for the art image query is proposed. The combined query method includes several steps: (1) Initial query. The tag query method and the semantic query method will be used. The initial query results include the results searched by both the methods. (2) Reorganization of the initial query results. The repeated images will be cleared and only one image will be left. (3) Distance based results rechecked. The most relative image will be ranked in front of the list and the less correlation image will be cleared. (4) Reordering the images. All the images will be reordered by the distance which reflects the correlation of the query image.

According to the experimental verification, the combined method can improve the query precision. In fact, due to the combined method add a step in the query process, the number of initial results will be increased. This is because of the addition of the images with less correlation. The combined method will almost add a specific time length to the total query time. Therefore, when the total query time is short the combined method will add a relatively long time.

References

[1] W. T. Lu, L. Li, J. X. Li, T. Li, H. G. Zhang and J. Guo, "A multimedia information fusion framework for web image categorization", Multimedia Tools and Applications, vol. 2014, no. 3, **(2015)**, pp. 1453-1486.

[2] X. Lu and W. W. Xing, "Multimedia Information Processing Introduction", Journal of Visual Languages and Computing, vol. 2014, no. 1, **(2014)**, pp. 1-1.

[3] X. Benavent, A. G. Serrano, R. Granados, J. Benavent and E. de Ves, "Multimedia Information Retrieval Based on Late Semantic Fusion Approaches: Experiments on a Wikipedia Image Collection", IEEE Transactions on Multimedia, vol. 2013, no. 8, **(2013)**, pp. 2009-2021.

[4] S. Semrau and T. Schmidt, "Particle image correlation spectroscopy (PICS): Retrieving nanometer-scale correlations from high-density single-molecule position data", Biophysical Journal, vol. 2007, no. 2, **(2007)**, pp. 613-621.

[5] M. Adriani and F. Arnely, "Retrieving images using cross-language text and image features", Accessing Multilingual Information Repositories, vol. 2006, **(2006)**, pp. 733-736.

[6] H. W. Yoo, D. S. Jang, K. K. Seo and M. E. Lee, "Retrieving images by comparing homogeneous color and texture objects in the image", International Journal of Pattern Recognition and Artificial Intelligence, vol. 2004, no. 6, **(2004)**, pp. 1093-1110.

[7] C. C. Chang, J. C. Chuang and Y. S. Hu, "Retrieving digital images from a JPEG compressed image database", Image and Vision Computing, vol. 2004, no. 6, **(2004)**, pp. 471-484.

[8] L. Tang, C. K. Wu and H. T. Tsui, "A novel algorithm for retrieving complete 3D structure from freely captured image sequences", Journal of Imaging Science and Technology, vol. 2004, no. 3, **(2004)**, pp. 251-259.

[9] P. Abry, J. Coddington, I. Daubechies, E. Hendriks, S. Hughes, D. H. Johnson and E. Postma, "Special Issue: Image Processing for Digital Art Work Foreword", Signal Processing, vol. 2013, no. 3, **(2013)**, pp. 525-526.

[10] S. C. Liu and W. H. Tsai, "Line-Based Cubism-Like Image-A New Type of Art Image and its Application to Lossless Data Hiding", IEEE Transactions on Information Forensics and Security, vol. 2012, no. 5, **(2012)**, pp. 1448-1458.

[11] B. A. Purdy, K. S. Jones, J. J. Mecholsky, G. Bourne, R. C. Hulbert, B. J. MacFadden, K. L. Church, M. W. Warren, T. F. Jorstad, D. J. Stanford, M. J. Wachowiak and R. J. Speakman, "Earliest art in the Americas: incised image of a proboscidean on a mineralized extinct animal bone from Vero Beach, Florida", Journal of Archaeological Science, vol. 2011, no. 11, **(2011)**, pp. 2908-2913

[12] X. M. Tian, Q. H. Jia and T. Mei, "Query Difficulty Estimation for Image Search With Query Reconstruction Error", IEEE Transactions on Multimedia, vol. 2015, no. 1, **(2015)**, pp. 79-91.

[13] Z. W. Ye, M. W. Wang, Z. B. Hu and W. Liu, "An Adaptive Image Enhancement Technique by Combining Cuckoo Search and Particle Swarm Optimization Algorithm", Computational Intelligence and Neuroscience, vol. 2015, **(2015)**.

[14] Y. H. Li, S. H. Xu, X. N. Luo and S. J. Lin, "A New Algorithm for Product Image Search Based on Salient Edge Characterization", Journal of the Association for Information Science and Technology, vol. 2014, no. 12, **(2014)**, pp. 2534-2551.

[15] Y. D. Zhang, X. P. Yang and T. Mei, “Image Search Reranking With Query-Dependent Click-Based Relevance Feedback”, IEEE Transactions on Image Processing, vol. 2014, no. 10, **(2014)**, pp. 4448-4459.
[16] V. Hollink, T. Tsikrika and A. P. de Vries, “Semantic Search Log Analysis: A Method and a Study on Professional Image Search”, Journal of the American Society for Information Science and Technology, vol. 2011, no. 4, **(2011)**, pp. 691-713.
[17] L. Hollink, G. Schreiber and B. Wielinga, “Patterns of semantic relations to improve image content search”, Journal of Web Semantics, vol. 2007, no. 3, **(2007)**, pp. 195-203.
[18] C. R. Cui, J. Ma, T. Lian, Z. M. Chen and S. Q. Wang, “Improving Image Annotation via Ranking-Oriented Neighbor Search and Learning-Based Keyword Propagation”, Journal of the Association for Information Science and Technology, vol. 2015, no. 1, **(2015)**, pp. 82-98.
[19] J. Huang, X. K. Yang, X. Z. Fang, W. Y. Lin and R. Zhang, “Integrating Visual Saliency and Consistency for Re-Ranking Image Search Results”, IEEE Transactions on Multimedia, vol. 2011, no. 4, **(2011)**, pp. 653-661.
[20] Z. B. Shi, X. Y. Sun and F. Wu, “Photo Album Compression for Cloud Storage Using Local Features”, IEEE Journal on Emerging and Selected Topics in Circuits and Systems, vol. 2014, no. 1, **(2014)**, pp. 17-28.
[21] S. M. Bhandarkar and F. Chen, “Similarity analysis of video sequences using an artificial neural network”, Applied Intelligence, vol. 2005, no. 3, **(2005)**, pp. 251-275.
[22] W. Ye, C. Paulson and D. Wu, “Target detection for very high-frequency synthetic aperture radar ground surveillance”, IET Computer Vision, vol. 2012, no. 2, **(2012)**, pp. 101-110.
[23] E. C. Underwood, S. L. Ustin and C. M. Ramirez, “A comparison of spatial and spectral image resolution for mapping invasive plants in coastal California”, Environmental Management, vol. 2007, no. 1, **(2007)**, pp. 63-83.
[24] J. Ahmad, A. S. Malik, M. F. Abdullah, N. Kamel and L. K. Xia, “A novel method for vegetation encroachment monitoring of transmission lines using a single 2D camera”, Pattern Analysis and Applications, vol. 2015, no. 2, **(2015)**, pp. 419-440.
[25] T. Elguebaly and N. Bouguila, “Model-based approach for high-dimensional non-Gaussian visual data clustering and feature weighting”, Digital Signal Processing, vol. 2015, **(2015)**, pp. 63-79.
[26] J. Herve, D. Matthijs and S. Cordelia, “Product quantization for nearest neighbor search”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 1, **(2011)**, pp. 117-128.
[27] L. F. Ai, J. Q. Yu, T. Guan and Y. F. He, “Adaptively Filtering Query Results for Large Scale Image Feature Retrieval”, Chinese Journal of Computers, vol. 37, no. 30, **(2014)**, pp. 1-12.

