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Research on New Multi-Feature Large-Scale Image Retrieval Algorithm based on Semantic Parsing and Modified Kernel Clustering Method

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Abstract

Because of the feature points can describe the local characteristics of the image in a reasonable manner, effective use of feature point of content based image retrieval become the current hot issues in the field of computer vision. Aiming at this problem, we put forward a kind of combination clustering based on feature points, a new method of image retrieval. The method includes the combination of feature point clustering algorithm and based on the algorithm of local color histogram construction strategy. With the existing and local color histogram retrieval method based on feature points, compared to the method can effectively solve the current method of feature point location information and feature point center relying too much on the problem. Subjectivity and as a result of the manual annotation image accuracy, the traditional image retrieval methods cannot meet the needs of the user. Multidimensional indexing technology is only from the perspective of how to improve the indexing algorithm to adapt to the large-scale database to consider a problem, in content-based image retrieval. Our research combines the advantages of the semantic analysis and kernel clustering which will enhance the performance of the traditional image retrieval methods and strengthen the feasibility of the algorithm.

Keywords: *Image Retrieval; Semantic Parsing; Kernel Clustering; Large-Scale; Feature Extraction; Multi-Feature; Randomly Scattered*

1. Introduction

With the advent of the era of multimedia, people increasingly come into contact with a lot of image information. These images randomly scattered throughout the world, however, or exist in a large image database [1]. The information contained in the image cannot be effectively access and use. This requires the ability to quickly and accurately access technology of image denoted as the image retrieval technology. Research in the field of image retrieval based on text, and based on the content divides into two broad categories. The original image retrieval method use traditional text retrieval techniques for image to text annotations to interpret the content of the image. The characteristics of this method are simple, easy to understand, but the several fundamental problems difficult to solve. The traditional text-based image retrieval technology is described by keyword or free text, and query operations are the base to the image or text description accurately matching probability matching. Text-based image retrieval method is simple and easy to understand, but to indicate the text retrieval characteristics. Subjectivity and as a result of the manual annotation image accuracy, the traditional image retrieval methods cannot meet the needs of the user. Relative to text-based image retrieval technique, content-based image retrieval has realized the automatic and intelligent image retrieval and management, mainly using some visual information of the image, such as color, shape,

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texture information as retrieval way, so as to improve and optimize the retrieval efficiency and accuracy to get more and more people off [2].

Before conducting research on the proposed algorithm, we firstly analyze the traditional methods of image retrieval. The traditional methodologies could be specifically separated into the following sub-sets. (1) Based on color feature retrieval. From the angle of human vision, color feature is a basic human perception and distinguish between different objects of visual features and also because of the color and colorful world. Color is a kind of important visual information attributes, relative to other features, color features of the size of the image itself, direction, angle of less dependence which has strong robustness and color features are simple for calculation, thus it becomes the most widely used approach in the existing retrieval system characteristics. The characteristics of the color expression depend on the color space. Not all of the color space is consistent with human visual perception. The study indicates that the human eye to color perception is three-dimensional. Match human visual model is the key to the use of color features for image retrieval [3-5]. Color histogram is the main idea according to the number of pixels of the same color proportion in the whole image. Then two images was measured using color histogram of color space information. Color histogram computation is simple, and has the scale, translation and rotation invariance. Color histogram holds main drawback: it contains only one color with the frequency and the pixel location information lost which could only give a picture of any image and its corresponding histogram, but different images may have the same histogram, that is to say, histogram and image is a one-to-many relationship, this is obviously not in conformity with human visual induction [6]. (2) Based on the morphological characteristics of retrieval. Shape is often associated with the target object and has the certain semantic meaning. Thus shape characteristics can be seen as more advanced than the color and texture features. To a certain extent, shape is the closest matching characteristics of user requirements. But in the shape of expression than the expression of color and texture in nature is much more complex. For the wider range of shape matching problem, need to begin from research deformation model. Elastic deformation model is the research and application of the earliest models, followed by active contour model is applied to the edge and contour retrieval. For retrieval based on shape, the shape of the extraction, description, and matching are the key to solve the problem [7-8]. Compared with the method of retrieval based on color and texture, the retrieval method based on shape is more difficult. (3) Retrieval based on texture feature. Texture is an important and difficult to describe the image features, many of the images may present the irregularity in local area, but on the whole show certain regularity. The texture characteristics are internal characteristics of the image, including roughness, directivity, contrast and regularity [9]. Texture feature is applicable to retrieve image categories such as water waves, cloth which contains the arranged on the surface of the structure and the relationship of the surroundings. Early studies of texture feature extraction are under the background and influence of pattern recognition. Typical representative is based on second order the statistical characteristics of gray level co-occurrence matrix. At the same time, the researchers will also wavelet transform technique is applied to texture analysis, and obtained good results [10]. (4) Based on spatial retrieval technology. Objects in the image space position and is the important information of the image of object relations, it embodies the image of the internal parts asked. To determine the image with empty depends on to the target object in the image, and the target object described by shape again [11]. So the extracted shape for the analysis of the spatial relationship is very important. (5) Image retrieval based on semantic analysis. Image retrieval based on semantic need to solve the problem of two aspects: one is to provide high-level semantic description, the second is must have the low-level image features are shot to the high-level semantic approach. Image visual feature information and understand the user's basic visual data inconsistencies which make visual semantic gap between low-level features and high-level semantic [12]. Based on the physical

characteristics of the lower retrieval, semantic feature retrieval is based on the text query which contains the natural language processing and the traditional image retrieval technology. The corresponding performance of the retrieval system is enhanced and optimized in the large extent and degree.

In the recent time, more and more semantic algorithms for image retrieval have been proposed with satisfactory performance. In [13], Tieniu Tan's research group conducted research on the deep semantic ranking based hashing for multi-label image retrieval. In their method and approach, deep convolutional neural network (DNN) is incorporated into hash functions to jointly learn feature representations and mappings from them to hash codes, which avoids the limitation of semantic representation power of hand-crafted features. Such statistics of each color image contains pixels and the polymerization rate is called the image pixels color aggregation vector. In [14], Eugene Santos Jr conducted research on automatic content based image retrieval using semantic analysis. They focus on fundamental semantic gap that exists between the low-level visual features of the image and high-level textual queries by dynamically maintaining a connected hierarchy in the form of a concept database. Extract the image semantic features are based on visual features of image with the text-based image retrieval has essential difference. The past the image retrieval based on text is simply mechanically string matching, and now the concept of semantic feature extraction is establish the mapping relationship between words and images. This is not a one-to-one mapping relationship, the same word in different image content can represent different meanings, and different text can also be said similar or the same content of the image. In [15], Anuja Khodaskar's research group theoretically analyzed the new-fangled alignment of ontologies for content based semantic image retrieval methodology. Shape matching is divided into two types based on boundary and area. Computer can automatically extract and directly identify the underlying characteristics of the image. But because the people in the image retrieval, image may not find the right sample. But only know some semantic concept. Stratified index is to accelerate retrieval and commonly used an indexing mechanism. For many retrieval operation, using the Euclidean distance calculation global statistical histogram matching. Characteristics of the calculation of the distance between the often require large amount of calculation. Respectively the Fourier descriptor and expression invariant moment features. Model method is fully automated, and the relative thoughts are the retrieval system of dynamic study based on user relevant feedback of learning the link between the semantics and visual features with automatic generation of mapping.

In this paper, we conduct theoretical research on the new multi-feature large-scale image retrieval algorithm based on semantic parsing and modified kernel clustering method. Efficient indexing technology is content based image retrieval can play advantage in large image databases. Indexing technology with the development of database technology and development is then applied to content-based image retrieval. Multidimensional indexing technology is only from the perspective of how to improve the indexing algorithm to adapt to the large-scale database to consider a problem, in content-based image retrieval, it is used to express the visual features of image content has its own representation method, it greatly increases the difficulty of the index. In the figure one, we demonstrate the sample framework of the semantic based image retrieval system. From the features of semantic description from the angle of the general convenient user query expression needs to consider, the image semantic classification is given the retrieval speed and accuracy. Despite the use of color histogram, texture, shape, model the visual features also can't accurately describe the meaning of the image, but still have a connection between semantic expression to do right now is how to extract more able to express human's image perception characteristics, how to make the meaning of these low-level visual features and image related more closely. This paper is organized as the follows. In the section two, we introduce some basic knowledge of the image clustering with kernel analysis and the principle techniques of the semantic analysis. In the section three, we

theoretically put forward the principle of our proposed algorithm. In the section four, we experimentally simulate the proposed approach with other state-of-the-art methods and draw the final conclusion in the last section with our prospect.

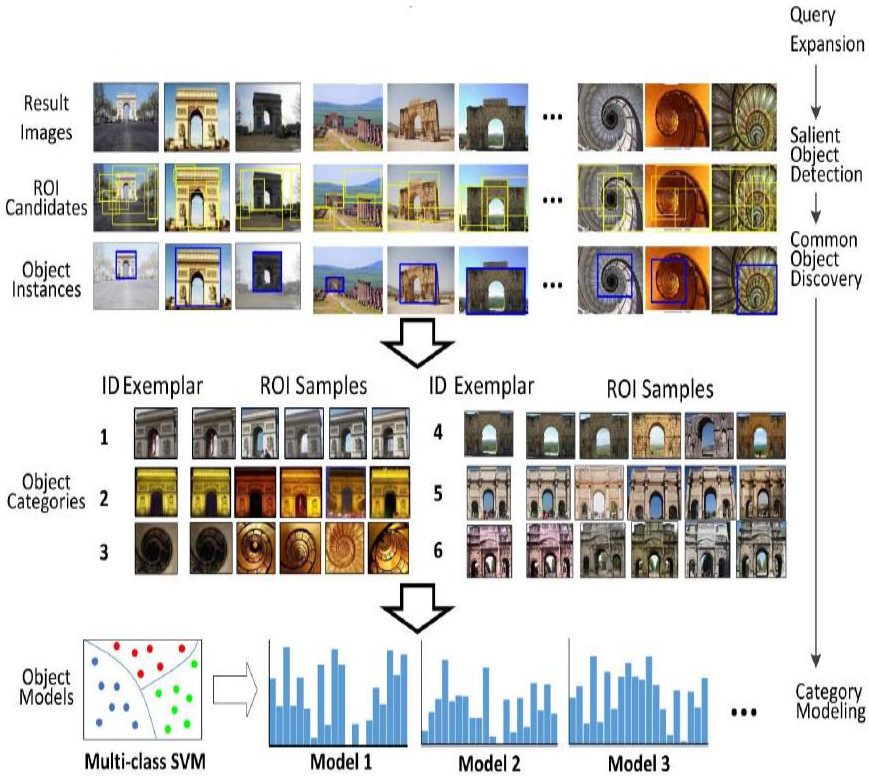

Figure 1. The Sample Framework of the Semantic based Image Retrieval System

2. The Basic Knowledge on Clustering and Semantic Analysis

2.1. The Kernel Clustering Algorithms for Image Retrieval

Commonly used image characteristics can be divided into global features and local characteristics. In recent years, studies have shown that local characteristics tend to be more applicable to describe the image content. In many local characteristics, feature points as part of the image visual information more outstanding can more effectively describe the local characteristics, thus is widely used in image retrieval. Combined clustering algorithm belongs to the core content, specific algorithm is described below.

$$d_w\left(a_i, a_j\right) = \sum_{\alpha=1}^{m} w_\alpha \left\| v_i^\alpha - v_j^\alpha \right\| \tag{1}$$

Knowing that the parameters of the model, we could refer to the model introduced belongs to each component of the probability of each data point. Then, modify the value of each component (where each component is suitable for the whole data set, and each point by belong to get the probability of the composition is good) and repeat the process until the end of convergence to conditions [16-19]. For the general Gaussian mixture distribution, random initialization parameters of the hybrid model, followed by probabilistic model for expression.

$$P_{ij} = P\left(x_j \mid C = i\right) P\left(C = i\right) \tag{2}$$

Texture is usually defined as the image of a local nature, the distribution of spatial information in an image is a certain degree of quantitative description and texture feature extraction in this paper is based on fractal dimension. But a lot of visual difference nature texture, the fractal dimension is approximately the same, as a result, a single fractal dimension cannot provide enough information to describe and identify the texture. Algorithm through the greedy algorithm to find out a covered each is at least a sample of the smallest rectangle in the package, and then use the rectangular ability to pick out the most difference between a set of attributes, on the basis of the rectangle is all package sample for the most likely extend continuously. Using the independent sample with assumptions and Bayesian formula density function problem is transformed into a function optimization problem, and finally in the sample space to find a place to meet, the point at which a neighborhood is far the most negative package. Both methods implicit requirements of sample space is potential are examples of package with empty clustering. Based on this understanding, this article, through clustering algorithm to obtain the potential positive sample center and bags of potential are representatives of the sample, and then construct suitable for clustering.

$$f(x_i) = \operatorname{sgn}[w \cdot x_i + b] = \begin{cases} 1 & , y_i = 1 \\ -1 & , y_i = -1 \end{cases} \tag{3}$$

Based on this understanding, is the sample clustering points within the set contains sample up to the clustering of is the potential for positive sample center. If the sample is in the center of the sample range, the example is a potential is sample. In package such as no sample in the center of the positive sample range and the center from the nearest point as a potential are examples. In the following equation, we describe the objective function for optimization.

$$\min \psi(w, \zeta) = \frac{1}{2}\|w\|^2 + c\sum \zeta_i \qquad s.t. \qquad y_i\left(w^T \psi(x_i) + b\right) \geq 1 - \zeta_i \tag{4}$$

With image contains several main color to express the information of color image, not only the extraction method is simple, and use the main color descriptors to describe color features can avoid the color histogram of the problem such as high storage space, large amount of calculation. It can not only make up for the gray-level histogram in express spatial location information, and can represent the direction of the gray image information, especially suitable for the marginal distribution of irregular natural images. Sliding structure element method, the calculation in which a group of the number of pixels with the same color in different scales within the scope of collecting the relative size of these regions and the frequency distribution, we establish the descriptions of color space distribution information [20-21]. By dual deformation, the optimization problem into:

$$\max \psi(\alpha) = \sum \alpha_i - \frac{1}{2}\sum\sum \alpha_i \alpha_j y_i y_j k\left(x_i, x_j\right) \qquad s.t. \qquad \sum \alpha_i y_i = 0 \tag{5}$$

Now focus on the kernel function in the application of the algorithm of ontology. But the kernel function is designed and the traditional heuristic method to calculate the similarity of different vertex asked, focus on the design about finding optimal optimization model on the nuclear matrix. Its design idea is: at the edge of the figure of ontology in the adjacent vertices to have high similarity, there is no edge adjacent vertices of similarity degree are relatively low. Image visual feature extraction and expression is the foundation of image retrieval technology. Effective visual feature extraction can improve the accuracy of image retrieval. But more than a single visual feature and traditional features fusion method is not enough to accurately comprehensively explain the similarity between image visual features. Gabor filter is made up of Gaussian function

after modulation, scaling and rotation generated by scale of a cluster system, complex contains real part and imaginary part which have strong selective frequency and direction. The formula 6 shows the function.

$$g(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)\right]\exp(2\pi iwx) \tag{6}$$

The image after discrete Gabor transform, in different directions and scales the size of the sequence can well represent the image energy. Therefore, this article based on the mean and standard variance of amplitude sequence as the texture feature of image, and uses the Gaussian normalization method to the texture characteristics of matrix. Based on the method of nuclear similarity calculation data in the statistical learning plays an important role can more accurately describe the image feature differences. Established such mixed nuclear features can full more accurate describe the differences between image visual feature and image, and the original space samples mapped to high-dimensional feature space which makes samples linearly separable. The figure two shows the result after the kernel clustering.

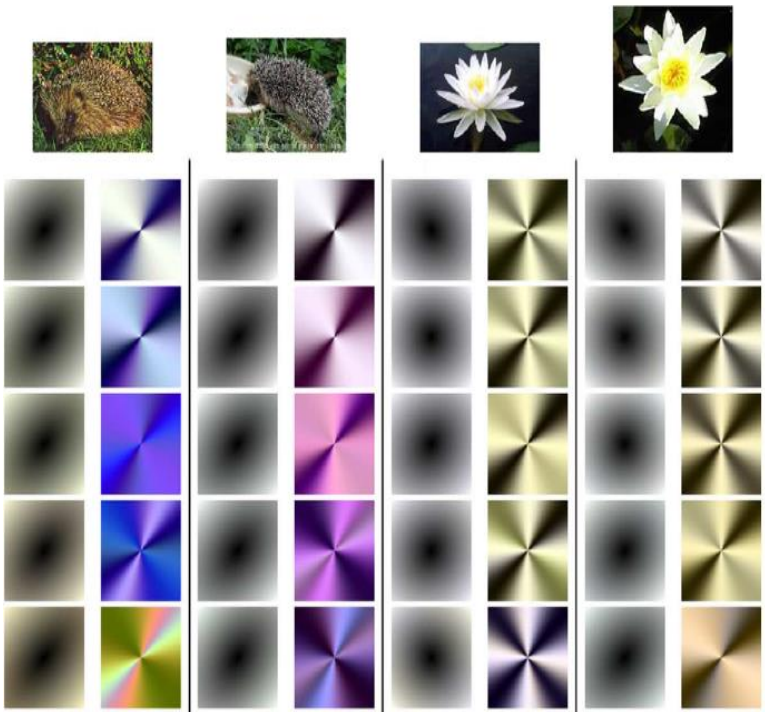

Figure 2. The Result of the Image after Kernel Clustering and Projection

2.2. The Semantic Analysis for the Image Retrieval

The image must be attached on all kinds of content including semantic information can truly support the semantic retrieval. It is important to provide the process of creating the content information. The method of using computer vision and machine learning to make the system for certain specific response is a lot of researchers for a long time efforts in the direction of the object recognition and scene recognition is part of it which make the ability of computer retrieval image close to people's understanding of the level that is the purpose of semantic image retrieval. According to the similar image area for first clustering, because some areas in the image is more important than other areas, so must be in the image of regional division value. In order to determine the value of image region in the first place in the area of the image clustering, then according to the information

retrieval based on term frequency and inverted document frequency weights calculation area. Finally each image with a semantic vector, vector of each said weights appear in the image of the area.

Image clustering is based on the similarity of the image, to calculate the similarity of images, to build an image of a feature vector. Existing image retrieval technology and system are generally under the demand to the semantics of a narrow application area respectively. To establish a more general image semantic retrieval system and supports a wide range of user requests for the whole process of semantic representation and processing for a certain abstract is very necessary. The image semantic extraction method could be summarized into the follows. (1) The use of system knowledge semantic extraction. Based on the semantic extraction of knowledge main feature is the need to advance to the system to provide the necessary knowledge Such as object template image scene classifier and so on. According to the semantic content of extract and adopt the method and can be divided into processing method and a global processing method based on object recognition. Semantic relative to the front of the image is more subjective several semantic, it relates to people's cognitive model of cultural background and aesthetic standards. At present only in the specific field of art image to image emotional semantic had a certain amount of research. (2) The generation of semantic system interaction. The current general fully automated image semantic processing there is still some insuperable barrier. In machine vision artificial intelligence development level of existing semantic processing which must fully consider the people treat people as a part of the system. Human interaction semantic extraction is mainly manifested in two aspects of image preprocessing and feedback learning. (3) Semantic extraction based on the external information. External information source of semantic extraction refers to according to the image of the other information sources to obtain relatively high-level description information.

To numerically describe the features of the semantic analysis, we firstly define the characteristics of the distance measurement as the formula seven.

$$Distance(p,q) = 1 - \left(\sum_{i=1}^{N} w_{pi} \times w_{qi} \right) / \left(\left(\sum_{l=1}^{N} w_{pl}^{2} \right) \cdot \left(\sum_{l=1}^{N} w_{ql}^{2} \right) \right) \tag{7}$$

Only with the bottom layer of a single color or high-level semantic features to retrieve, the experiments prove that the retrieval result is not ideal, therefore, adopts the combination of the bottom color and high-level semantic feature integrated waste line algorithm, and set up the right will be the linear combination of different to realize image movement, namely the fusion feature retrieval method. Its essence is the expansion of single feature. The corresponding semantic similarity metric measurement criteria are shown below.

$$d(p,q)^{[n]} = \left(\frac{d(\mathrm{p},\mathrm{q}) - m_d}{3\sigma_d} + 1 \right) / 2 \qquad p = 1, 2, \cdots, n \tag{8}$$

$$D_M(p,q) = w_c d_c^{'} + w_s d_s^{'}, \quad w_s + w_c = 1 \tag{9}$$

Due to all areas of the retrieved images in accordance with the image area for the node, regional matching the value of the network, as adjacent edge build is also regarded as a kind of complex network, and prove that complexity is a small world network trap that is defined. So by sub network segmentation algorithms, the complexity of the network is divided into multiple child network, every child network as made up of similar semantic area through the semantic learning algorithm, then the complexity of the network of semantic concepts and stored in a database, in order to match the future similar content of

the image retrieval. In the following figure three we demonstrate the semantic features of the large-scale images.

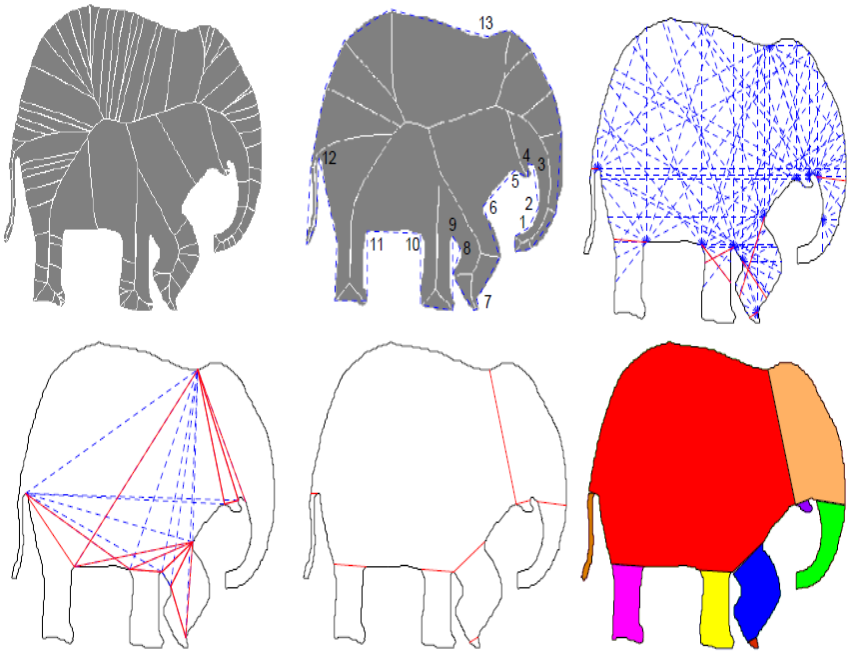

Figure 3. The Sample Semantic Features of the Large-scale Images

All the low-level features of images in the image library to extract, clustering for these low-level features similar areas. For a class the same semantic concepts to express and those who contain the same image of high-level semantic description words also have similar low-level feature area. That is to say, with similar characteristics of low-rise area often use the same high-level semantic description [22-24]. Create a visual thesaurus and it will contain the image repository can meet most of the normal block types. Then, through the pattern vector form one that is associated with a given image visual dictionary. Our research purpose is to retrieve the semantic similar images. When we went to retrieve a given image, the image of the semantic description and return the image semantic concept phase at the same time which is considered to be related. If the visual effect of image similar, but different semantic concepts, as these images are not related. The sets definition is shown in the formula 10.

$$sub-block-sets = \{ sbs_{ij} \mid sbs_{ij} \subset I_i \} \tag{10}$$

Semantic description of target shape is a very complicated problem, in fact, has yet to find an exact definition of the shape, including geometry, statistics or morphology measure to consistent with the person's feeling. People's sense of the shape is not only a physiological reaction results in the retina, and the experience and knowledge about the real world of retina between comprehensive results which will be shown in the next section.

3. The Proposed Algorithm

3.1. The Multi-Feature Large-Scale Image Characteristics

In the process of image retrieval, database management, organization, quality directly affects the efficiency of retrieval. Because of large scale image library basically corresponding to the features of a large library, right of access and index classification is

very important. However the image as an intuitive and simple method of stored information, become an important part of the database, but its capacity is big, the efficiency of image retrieval is very low. How to establish an effective index structure in image database is the key to improve the efficiency of retrieval. Commonly used methods for image retrieval based on single feature clustering. Multimedia retrieval system based on image text description is the use of mature development evolution based on text information retrieval technology, it is important to the description of the key, the first description of every image keyword and then using full-text retrieval based on text information retrieval technology. Multimedia image retrieval system is the core of image features extracted the characteristics of the library. Image features if master is used to calculate the distance between the image and the image similarity.

It is a two-way relationship between the user and the image retrieval system: first, the user query request, the system according to the requirements return query retrieval results and then the user can also interact with the system according to the result of returning the relevant feedback to improve the retrieval results. The follows formulas define the color matrix.

$$s_i = \left(\frac{1}{N} \sum_{j=1}^{N} \left(P_{ij} - \mu_i \right)^3 \right)^{1/3} \tag{11}$$

$$\Theta_i = \left(\frac{1}{N} \sum_{j=1}^{N} \left(P_{ij} - \mu_i \right)^2 \right)^{1/2} \tag{12}$$

Organization arrangement of texture feature contains object structure and links with the surrounding environment, therefore widely used in multimedia image retrieval. Texture characteristics in the field of pattern recognition, computer vision has many applications, based on its improved application in the field of multimedia image retrieval, the user can by submitting a texture image to find similar other images. Image retrieval in multimedia retrieval based on color, texture and shape are to be carried out some aspect of image feature extraction, and feature vector with the increase of the image, form the "dimension disaster", high dimension increased the complexity of the calculation at the same time reduce the classification performance in the retrieval process, that is known for the training sample, there is a limit, when the use of the characteristics of number exceeds the ceiling, classification will be degraded. For instance, we distinguish between "beef" and "pork", texture and length-width ratio are good characteristics of images, then the auxiliary judgment by color, basic can implement retrieval recognition, but if an increase in volume, weight and other features may cause interference to classification, based on this reason remove interference becomes a research direction, the most effective method is the dimension reduction of the image. The idea of dimension reduction is achieved by function mapping from high dimension space to low dimension space denote as the Formula 13.

$$F(x) = \begin{Bmatrix} F_1(x) \\ F_2(x) \\ \vdots \\ F_n(x) \end{Bmatrix} = \begin{Bmatrix} F_1(x_1, x_2, x_3, \cdots x_m) \\ F_2(x_1, x_2, x_3, \cdots x_m) \\ \vdots \\ F_n(x_1, x_2, x_3, \cdots x_m) \end{Bmatrix} \tag{13}$$

This algorithm firstly will make certain assumptions in embedded map or low dimensional manifold aspects, or be able to maintain a certain property of high-dimensional data remains the same: and then through the internal data structure of the nonlinear manifold, map the data dimension reduction problem is transformed into solving eigenvalue problem and does not require iteration method, finally we can get a

low-dimensional subspace of non-linear. The advantage of such a nonlinear algorithm is in most data can reflect the nature of the data.

3.2. The Semantic Parsing and Kernel Clustering based Algorithm

In content-based image retrieval system need to define a distance measure to calculate the similarity between two images relative distances between the query image and the target image, thus finding the most similar images with the query image. Description based on the histogram of image content, the simplest method is direct histogram similarity matching. The traditional histogram method due to the information does not include the image pixel space, affecting the precision of the retrieval and correctness. Because traditional color histogram can only record the overall image, so with the same histogram of the image may be very different from the semantics. Texture area of high frequency and low frequency, for example, the natural scene can have similar or even identical color histogram. This problem is especially critical in a large database, including many of the images have similar histograms, make it to a lack of discrimination in the retrieval of large image database and not well match human visual and the color histogram is highly dependent on the color code this design, and is sensitive to quantify boundary. Because the color of color close may be due to quantify is divided into different handle. Image is closely related to the content of the description and image data representation. Usually in the compressed format image database storage, it is difficult to directly extract content characteristics and the decoding characteristics after extraction efficiency is very low, because the decoding will spend extra time. Directly from the content of the compressed image to extract the image feature has been research direction.

According to the mentioned semantic parsing and kernel clustering methodologies, the overall similarity definition is shown in the following formula [26-29].

$$D(P,Q) = p^T S_{11} p + q^T S_{22} q - 2 p^T S_{12} q = \sum_{i=1}^{M}\sum_{k=1}^{M} a_{ik} p_i p_k + \sum_{j=1}^{N}\sum_{l=1}^{N} b_{jl} q_j q_j - 2\sum_{i=1}^{M}\sum_{j=1}^{N} c_{ij} p_i q_j \quad (14)$$

Based on wavelet coding model not only provides the coding efficiency and new features, such as adjustable resolution and quality, and wavelet coding bit stream can be progressive decoding, some resolution of image content can at some point in the decompression and easily accessed. So based on the characteristics of the wavelet image compression coding description and extraction algorithm has more and more get people's attention. Said based on the characteristics of the wavelet transform can also provide the resolution and quality of the adjustable and progressive image similarity matching, improve the matching efficiency of image retrieval. The real content based image retrieval system need high level abstract image characteristics. But the current state of the is, apart from a few narrow definition of specific application field, most of the available features are low to intermediate level of abstract level. Low-level features cannot create enough only and accurate representation of the original image using the low-level features such as color histogram and statistical features in capture when don't need the space information, but it's hard to image matching and retrieval result is satisfactory. In the following figure, we illustrate the flowchart of the proposed algorithm.

Input: training feature vectors $\mathcal{X} = \{\boldsymbol{x}_i \in \mathbb{R}^d\}_{i=1}^n$, label matrix $S \in \mathbb{R}^{l \times l}$, old hash functions $h(\boldsymbol{x})$ if updating
initialize $R_0 = rS$ and $T_{max} = 500$;
for $k = 1; k \leq r$ **do**
  if *is updating* **then**
    $\boldsymbol{a}_k^0 \leftarrow \boldsymbol{a}_k^\star$;
  end
  else
    solve the generalized eigenvalue problem $\bar{K}_l^\top R_{k-1} \bar{K}_l \boldsymbol{a} = \lambda \bar{K}_l^\top \bar{K}_l \boldsymbol{a}$ obtaining the largest eigenvector $\boldsymbol{a}_k^0$ such that $(\boldsymbol{a}_k^0)^\top \bar{K}_l^\top \bar{K}_l \boldsymbol{a}_k^0 = l$;
  end
  use the gradient descent method to optimize $min_a - (\varphi(\bar{K}_l \boldsymbol{a}_k))^\top R_{k-1} \varphi(\bar{K}_l \boldsymbol{a}_k)$ with the initial solution $\boldsymbol{a}_k^0$ and T_{max} budget iterations, achieving $\boldsymbol{a}_k^\star$;
  $h^0 \leftarrow sgn(\bar{K}_l \boldsymbol{a}_k^0) \quad h^\star \leftarrow sgn(\bar{K}_l \boldsymbol{a}_k^\star)$;
  if $(h^0)^\top R_{k-1} h^0 > (h^\star)^\top R_{k-1} h^\star$ **then**
    $\boldsymbol{a}_k^\star \leftarrow \boldsymbol{a}_k^0 \quad h^\star \leftarrow h^0$
  end
  $R_k = R_{k-1} - h^\star (h^s tar)^\top$;
end
Output: r hash functions $\{h_k(\boldsymbol{x}) = sgn(\bar{\boldsymbol{k}}^\top(\boldsymbol{x}) \boldsymbol{a}_k^\star)\}_{k=1}^r$

Figure 4. The Flowchart of the Proposed Image Retrieval Algorithm

4. The Experiment Analysis

4.1. The Set-up of the Experiment

In this section, we will conduct numerical simulation on the proposed algorithm, based on the above ideas, implements a prototype system. The system of experimental environment is the Intel P4 3.0 GHz, Windows Win 7, 8 GB of memory. Experiment test adopted by the image library mainly comes from Corel image library and millions of atlas website, a total of 4000 images that are divided into 40 classes, each class the number of images to between 20 and 130. Color model to quantify the image color information, and extract the main color with fixed 8 main colors, and by intersecting histogram matching, we put forward a kind of effective primary color clustering index retrieval algorithm, only need to retrieve picture when image retrieval belonging to a cluster of image retrieval, ignore other images of the clustering, avoided to the large number of similar images retrieval invalid, thus greatly improving the retrieval effectiveness and efficiency [30-31]. In the next following sub-section, we will numerically analyze the simulation result.

4.2. The Statistical Result of the Experiment

In this section, we demonstrate the numerical simulation result for our proposed algorithm. In the Figure 5, we show the database adopted by the experiment, the databased is made up of 500 individual pieces that contain various features and characteristics. In the Figure 7, we show the result of capturing features and corresponding semantic meaning of the images. The Figure 6 represents the statistical result for the experiment whereas the final figure illustrates the corresponding curve of the experiment. It could be reflected from the images that the proposed method performances better compared with other state-of-the-art algorithms.

Figure 5. The Databased Adopted by the Experiment

Corel	MAP@5			MAP@10			MAP@15			MAP@20		
	TagProp	TagRel	TMC	TagProp	TagRel	TMC	TagProp	TagRel	TMC	TagProp	TagRel	TMC
r=1	47.95	47.84	49.48	41.85	41.83	45.01	36.60	37.01	39.24	30.98	31.14	33.52
r=2	48.99	49.98	59.36	43.70	44.71	53.00	37.58	38.14	47.48	32.50	33.39	41.13
r=3	57.52	58.27	70.60	52.16	52.48	64.17	46.54	47.38	59.02	41.34	42.31	52.93
r=4	60.23	62.25	74.99	55.07	56.53	67.73	50.07	52.25	62.13	44.41	46.69	55.99
Labelme	MAP@5			MAP@10			MAP@15			MAP@20		
	TagProp	TagRel	TMC	TagProp	TagRel	TMC	TagProp	TagRel	TMC	TagProp	TagRel	TMC
r=1	50.12	50.33	52.18	43.78	43.81	47.33	41.87	41.67	42.47	35.63	35.12	37.87
r=2	51.56	52.33	62.26	45.22	46.27	55.67	42.21	43.34	50.37	37.83	37.91	44.76
r=3	59.33	61.53	72.28	54.73	54.89	66.36	51.33	52.65	62.87	46.77	45.28	55.72
r=4	62.65	65.78	76.82	57.91	58.18	69.59	56.41	57.27	65.58	50.36	51.27	57.99
r=5	67.14	68.96	80.03	63.36	63.76	72.14	59.18	59.73	68.34	53.12	54.16	60.03
Flickr	MAP@5			MAP@10			MAP@15			MAP@20		
	TagProp	TagRel	TMC	TagProp	TagRel	TMC	TagProp	TagRel	TMC	TagProp	TagRel	TMC
r=1	61.65	62.09	71.26	61.18	61.54	71.23	60.55	61.16	69.13	57.35	58.01	70.02
r=2	72.33	73.27	78.91	71.83	71.93	78.86	71.54	71.97	78.55	69.10	69.91	76.76
r=3	76.48	77.75	83.83	76.36	77.17	83.59	75.47	76.52	81.37	71.77	72.28	83.72
r=4	78.96	79.98	86.78	78.82	79.08	86.61	77.35	77.87	84.91	76.41	76.27	80.99
n=5	80.87	81.16	88.53	80.45	80.76	88.52	79.99	80.57	86.39	76.74	77.16	86.03
TinyImg	MAP@5			MAP@10			MAP@15			MAP@20		
	TagProp	TagRel	TMC	TagProp	TagRel	TMC	TagProp	TagRel	TMC	TagProp	TagRel	TMC
r=1	50.11	51.15	61.16	48.32	48.11	58.13	43.32	42.13	49.21	40.23	40.33	45.11
r=2	61.23	62.43	65.21	58.25	58.23	61.58	50.54	50.42	56.34	47.57	47.46	52.25
r=3	65.54	66.22	69.43	63.36	64.43	64.62	58.67	58.15	61.53	53.86	54.75	58.64
r=4	67.65	68.34	71.76	64.76	65.77	67.23	60.22	61.64	65.55	56.35	57.23	61.21
r=5	69.66	70.52	73.54	66.77	67.56	69.74	62.37	62.67	67.37	60.31	61.44	64.61

Figure 6. The Statistical Experiment Result of the Proposed Method with Others

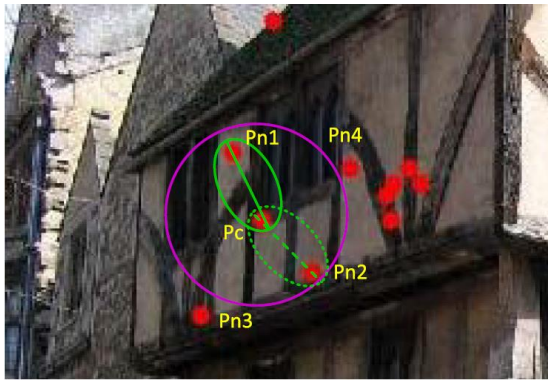

Figure 7. The Domonstration of the Feature Extraction and Semantic Analysis Steps

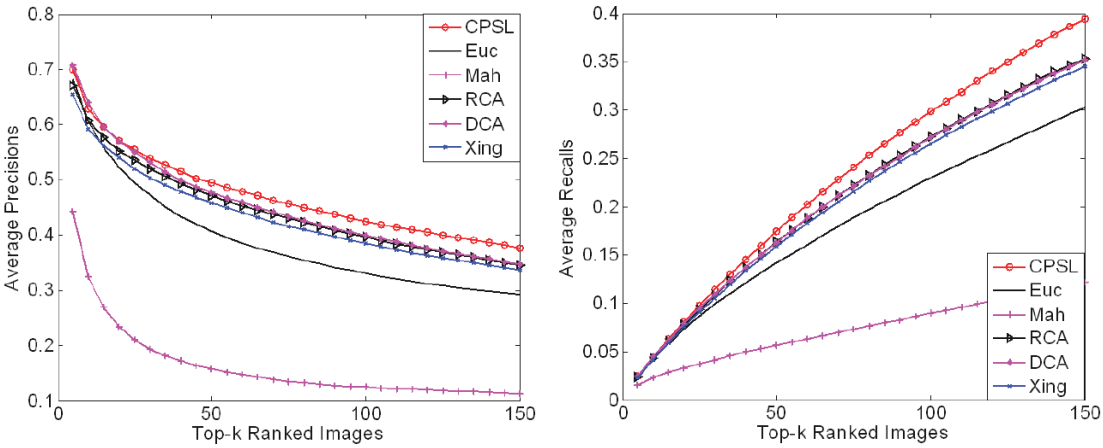

Figure 8. The Visible Result of the Experiment Compared with the Other State-of-the-Art Algorithms

5. Conclusion and Summary

In the paper, we conduct theoretical research on new multi-feature large-scale image retrieval algorithm based on semantic parsing and modified kernel clustering method. Based on the morphological characteristics of retrieval, shape is often associated with the target object and has the certain semantic meaning. Thus shape characteristics can be seen as more advanced than the color and texture features. Description based on the histogram of image content, the simplest method is direct histogram similarity matching. The traditional histogram method due to the information does not include the image pixel space, affecting the precision of the retrieval and correctness. Through the experimental simulation of the proposed methodology we could conclude that our algorithm performances better compared with other state-of-the-art methodologies which holds special meaning.

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