An Image Retrieval Technique Using Multimedia Features and SVM Classifier

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ABSTRACT

CBIR has been a very effective research area. CBIR is the mainstay of current image healing system. The purpose of CBIR is to current an image conceptually, with a set of low-level visual appearance such as color, texture, and shape. The computational intricacy and retrieval efficiency are main problems in CBIR. To avoid this problem, this paper administers an overview on a new content-based image comeback method using color and texture feature with SVM. In order to narrow the gap between user query perception and low-level features in content-based image comeback, the support vector machine (SVM) based technique is introduced. Therefore, to test the effectiveness in CBIR, a SVM based classification theory is adopted in CBIR to boost image comeback accuracy.

Keywords - CBIR, feature extraction, similarity matching, SVM.

I. INTRODUCTION

Image databases and collections can be enormous in size, containing hundreds, thousands or even millions of images. Currently under development, even though several systems exist, is the retrieval of images based on their fulfilled, called Content Based Image Retrieval, CBIR.[1] A huge amount of Image databases are added every minute and that is why it is the need for effective and profitable image betterment systems. There are many features of content-based image betterment but four of them are treated to be the main features. They are color, character, shape, edge direction and spatial properties [2]. Spatial equity, however, are essentially taken into narrative so the main features to consider are color, texture and shape. A typical CBIR uses the capacity of an image to perform and access. CBIR systems extract features like color, balance, and shape from images in the database placed on the value of the image pixels. These characters are smaller than the image size. These characters are stored in a database called character database. Thus the feature database enclose an absorption of the images in the image database; each image is represented by a crowded representation of its capacity that is color, texture, shape, and spatial instruction. This is called offline feature derivation. The main asset of using CBIR system is that the system uses image features alternately of using the image itself. So, CBIR is competitive, fast, and adequate over image search methods. All CBIR produce view the query image and the fetch images as a collection of features. These appearance, or image signatures, characterizes the fulfilled of the image. The advantages of using image appearance instead of the authentic image constituent appear in image representation and contrast for recapture. When the scheme uses image appearance for matching, it almost does confining for the image and use the most important fulfilled of the image [3]. This also platform the gaps between the high level approach and low level character. Several methods for fetch images on the basis of color similarity are actuality used. Each image added to the database is evaluated and a color feature is gauge which shows the capacity of pixels of any color within the image. Then this color feature for each image is reserved in the database. During the search time, the user can either specify the covet proportion of any color or submit an allusion image from which a color aspect is calculated. The matching process then recaptures those images whose color contests those of the query most closely. The capability to match on texture similarity can regularly be useful in different between areas of images with similar color. A collection of techniques has been used for character similarity. Texture similarity means calculate the related brightness of elected pairs of constituent from each image [4]. From these it is available to calculate image balance measures such as the degree of disparity, coarseness, revolution, directionality and randomness, directionality and regularity. In familiar, the purpose of CBIR is to begun an image conceptually, with a set of low-level visual looks such as color, texture, edge guidance and shape. These conventional accession for image retrieval are occupying on the computation of the affinity between the user’s inquiry and images via a query by example system. Despite the capacity of the search strategies, it is very ambitious to obtain the accurate healing result of CBIR within only one query action. The problem is that
the derive visual features are too diverse to capture the approach of the user’s query. To solve such problems, in the QBE system, the users can pick up some adopted images to clarify the image explorations iteratively. The feedback agenda, called Relevance Feedback (RF), repetition until the user is fulfilled with the retrieval results. In purpose feedback-based approaches, a CBIR system determine from feedback afford by the user. The learning is categorized into short-term learning, and long term learning. Relevance feedback has achieve much attention in the analysis and development of content-based image healing systems [9]. Although a number of RF studies have been made on CBIR, they still having some frequent problems such that existing RF design focus on how to earn the user’s satisfaction in one query growth. That is, existing methods clarify the query again and again by analyzing the definitive relevant images prefer up by the users. Especially for the admixture and complex images, the users potency go through a long series of feedbacks to obtain the crave images using current RF approaches. But it is not adequate in real applications. Existing purpose feedback-based CBIR methods usually appeal a number of iterative feedbacks to produce cultivated search results, especially in a large-scale drawing database. This is impractical and faulty in real applications. So it is necessary to curtail the number of feedback.

II. RELATED WORK

For color feature Ahmed J. Afifi, Wesam M. Ashour used color moment method because it has the lowest feature vector dimension and lower computational complexity. To extract the color features from the content of an image, Ahmed J. Afifi, Wesam M. Ashour need to select a color space and use its properties in the extraction. For texture feature Ahmed J. Afifi, Wesam M. Ashour used Ranklet transform. Before extract the texture feature from the image, perform a preprocessing step using Ranklet Transform. The result of applying Ranklet Transform on the image is 3 ranklet images in different orientation (vertical, horizontal, and diagonal)[3]. The concept of relevance feedback was introduced into CBIR from the concept of text-based information retrieval in the 1998’s [5] and then has become a popular technique in CBIR. By using relevance feedback, Content-Based Image Retrieval (CBIR) allows the user to retrieve images interactively. Begin with a coarse query, the user can select the most relevant images and provide a weight of preference for each relevant image to refine the query. The high level concept born by the user and perception subjectivity of the user can be automatically captured by the system to some degree. Pengyu Hong, Qi Tian, Thomas S. Huang proposes an approach to utilize both positive and negative feedbacks for image retrieval. Support Vector Machines (SVM) is applied to classifying the positive and negative images. The SVM learning results are used to update the preference weights for the relevant images[6]. For using relevance feedback to improve the retrieval accuracy, Dewen Zhuang, Shoujue Wang refined the visual features extracted based on linear discriminant analysis algorithm Dewen Zhuang, Shoujue Wang segment image into main region and margin region for cognition the whole image characteristic. To extract image features, Dewen Zhuang, Shoujue Wang select the width of margin as 0.1 of image size according to the experiment results. Color histogram is one commonly used visual features and has a computation simple but efficient characteristics. Owing some color spaces(e.g. LUV, HSV) seem to coincide better with human perception than the basic RGB color space, so Dewen Zhuang, Shoujue Wang use HSV color space for histogram-based descriptors. [7]. Yuki Sugiyama, Makoto P. Kato et.al. propose relative relevance feedback for image retrieval that aims to capture the relativity of positive and negative examples in search result pages. Given positive examples, the only thing is that selected items are more similar to an ideal query than items that are not selected as relevant [10].

III. PROBLEM DEFINITION

Early studies on CBIR used a single visual content such as color, texture, or shape to describe the image. The drawback of this method is that using one feature is not enough to describe the image since the image contains various visual characteristics. The computational complexity and the retrieval accuracy are the main problems that CBIR systems have to avoid. Early studies on CBIR used a single visual content such as color, texture, or shape to describe the image. The drawback of this method is that using one feature is not enough to describe the image since the image contains various visual Characteristics. The result of using multiple
feature are more accurate than using only one feature [3]. The conventional approaches for image retrieval are based on the computation of the similarity between the user’s query and images. Despite the power of the search strategies, it is very difficult to optimize the retrieval quality of CBIR within only one query process. The hidden problem is that the extracted visual features are too diverse to capture the concept of the user’s query[5]. It is necessary to retrieve the image by considering the user feedback. But the problem is that this method requires the more number of feedback. So it is necessary to reduce the number of feedback. Extracting multimedia data from the large multimedia repository suffer from problem such as redundant browsing and exploration convergence. Whenever the user query the database the resultant data is irrelevant with the user’s query and it takes long iterations of feedback to produce the result. The goal is to assist the search strategy in efficiently hunting the desired images.

PROPOSED SYSTEM

In this paper provides an overview on a new content-based image retrieval method using color and texture feature with relevance feedback and SVM. In order to narrow the gap between user query concept and low-level features in content-based image retrieval, the support vector machine (SVM) based relevance feedback technique is introduced. However, images with special spectral features. Relevance feedback mechanism hasn’t been widely used in content-based image retrieval (CBIR). Therefore, to test the effectiveness in CBIR, a SVM based relevance feedback algorithm based on SVM classification theory is adopted in CBIR to boost image retrieval accuracy.

IV. METHODOLOGY

The current state of the content-based image retrieval The history of the content-based image retrieval can be divided into three phases:
• The retrieval based on artificial notes.
• The retrieval based on vision character of image contents.
• The retrieval based on image semantic features.
The image retrieval that is based on artificial notes labels images by using text firstly, in fact it has already changed image retrieval into traditional keywords retrieval. There are two problems remain in this method.

On the one hand, it brings too heavy workload. On the other hand, it still remains subjectivity and uncertainty. Because the image retrieval that is based on artificial notes still remains insufficiency, the farther study that adapts vision image features has been come up and become the main study. The character of this method is image feature extraction impersonally, whether the retrieval is good or not depends on the accuracy of the features extraction. So the research based on vision features is becoming the focus in the academic community. The feature of vision can be classified by semantic hierarchy into middle level feature and low-level feature. Low-level feature includes color, texture and inflexion. Middle level involves shape description and object feature.

FEATURES EXTRACTION

Feature extraction is the heart of the content based image retrieval. As we know that raw image data that cannot used straightly in most computer vision tasks. Mainly two reason behind this first of all, the high dimensionality of the image makes it hard to use the whole image. Further reason is a lot of the information embedded in the image is redundant. Therefore instead of using the whole image, only an expressive representation of the most significant information should extract. The process of finding the expressive representation is known as feature extraction and the resulting representation is called the feature vector [11]. Feature extraction can be defined as the act of mapping the image from image space to the feature space. Now days, finding good features that well represent an image is still a difficult task. In this paper, a wide variety of features are used for image retrieval from the database. Image content can distinguish between visual and semantic content. Features usually represent the visual content. Visual content can be further divided into general or domain specific. For example the features that can use for searching would be representing the general visual content like color, texture, and shape. Another side, the features that are used for searching human faces are domain-specific and may include domain knowledge. If we talk about the semantic content of an image is not simple to extract. Annotation and/or specialized inference procedures based on the visual content also help to some extent in obtaining the semantic content [2]. The main point for choosing the features to be
extracted should be guided by the following concerns: The features should carry sufficient information about the image and should not require any domain specific knowledge and it should be easy to compute in order for the approach to be feasible for a large image collection and rapid retrieval. Another thing is that it should relate well with the human perceptual characteristics since users will finally determine the suitability of the retrieved images.

1. **COLOR FEATURE**
One of the most significant features of image that make possible the recognition of images by humans is color[9]. Color is a property that depends on the reflection of light to the eye and the processing of that information in the brain. We use color every day to tell the distinction between objects, places, and the time of day .Images characterized by color features have many advantages: Efficiency:-There is high percentage of relevance between the query image and extracted matching images. Strength:-The color histogram is invariant to rotation of the image on the view axis and changes in small steps when rotated otherwise or scaled .It is also not sensitive to changes in image and histogram resolution and occlusion. Simplicity:-The construction of the color histogram is a simple process, including scanning the image, the resolution of the histogram, assigning color values to, and building the histogram using color components as indices. Low Storage Requirements: - The color histogram size is significantly smaller than the image itself, because of color quantization.

2. **TEXTURE FEATURE**
In the field of computer vision and image processing there is no exact definition of texture [4,8].Because available texture definitions are based on texture analysis methods and the features extracted from the image. Texture is a main component of human visual perception. Like colour, this also makes it an essential feature to consider when querying image databases. Everyone can recognise texture but, it is not easy to define. Unlike colour, texture occurs over a region rather than on a point. It is normally defined purely by grey levels and as such is orthogonal to colour. Texture has qualities like periodicity and scale; it can be described in terms of coarseness, direction, contrast. However texture can be considered as repeated patterns of pixels over a spatial domain, of which the addition of noise to the patterns and their repetition frequencies result in textures that can become visible to random and unstructured. Or in other word we can say that texture is that innate property of all surfaces that describes visual patterns, each having properties of homogeneity. It contains important information related to the structural arrangement of the surface, such as; clouds, leaves, bricks, fabric. It also describes the relationship of the surface to the surrounding environment [7]. Basically two primary issues in texture analysis during similar image retrieval. Texture classification is concerned with identifying a given textured region from a given set of texture classes. Each of these regions has unique texture quality. Basically Statistical methods are extensively used like GLCM, contrast, entropy, homogeneity. Another is texture segmentation is concerned with automatically determining the boundaries between various texture regions in an image.

3. **SHAPE FEATURE**
Another major image feature is the shape of the object contained in the image Shape feature of image may be defined as the characteristic surface configuration of an object; an outline or contour. It permits an object to be distinguished from its surroundings by its outline [6,10] Shape representations can be generally divided into two categories: Boundary-based, and Region based. Boundary-based shape representation only uses the outer boundary of the shape. This is done by describing the considered region using its external characteristics, like the pixels along the object boundary. But the Region-based shape representation is totally dissimilar from the prior method .It uses the entire shape region by describing the considered region using its internal characteristics; i.e., the pixels contained in that region .The shape of an object is a binary image representing the extent of objects. In region-based considers the shape being composed of a set of two-dimensional regions, while the boundary based representation presents the shape by its outline. While in region-based feature vectors often result in shorter feature vectors and simpler matching algorithms. However, generally they fail to produce well-organized similarity retrieval. On the other hand, feature vectors extracted from boundary-based representations provide a richer description of the shape.
This scheme has led to the development of the multi-resolution shape presentations, which proved very useful in similarity assessment.

V. SVM

The importance of having good similarity measures for any feature set cannot be overemphasized. Although simple ranking methods based on for e.g. L1− and L2−norm have provided good results for single query images, they are not easily adaptable for multiple query images or for performing relevance feedback. Here we use Support Vector Machines (SVM) which have proved to be very adaptable to various machine learning tasks. Firstly we use a two-class SVM classifier in which we interpret CBIR as a two class classification problem, the two classes being the relevant (positive) and the not relevant (negative) images. Initially the classifier is trained using a few random images labeled by the user. Two-class SVM solves a classification problem by finding a maximum margin hyper plane that separates the positive training instances from the negative ones. Each training instance is represented as a vector $x \in \mathbb{R}^n$ and belongs to one of the two classes $L = \{-1, 1\}$. The instances lying closest to the hyper plane are called support vectors and are the only vectors affecting the hyper plane. In many cases the training instances would not be linearly separable in the original feature space $\mathbb{R}^n$. In this case they can be transformed nonlinearly into a higher dimensional feature space $\mathcal{F}$ with a mapping.

$$\phi : \mathbb{R}^n \rightarrow \mathcal{F}$$

$$x \mapsto \phi(x)$$

One obtains then a classification function of the form $f(x) = \text{sgn}(w \cdot \phi(x) + b)$. Through the use of a kernel $k(u, v) = \phi(u).\phi(v)$ different boundaries can be obtained. In fact, the kernel function $k$ would lead to classifiers with maximum margin in some mapped feature space even if the mapping $\phi$ itself is not analytically defined, as long as the kernel satisfies Mercer’s condition (Mercer, 1909). It should be noted that just correct classification is not the goal of a general purpose CBIR system, as the concept of classes does not exist here in the strict sense.

VI. CONCLUSION

The dramatic rise in the sizes of images databases has stirred the development of effective and efficient retrieval systems. The development of these systems started with retrieving images using textual connotations but later introduced image retrieval based on content. This came to be known as Content Based Image Retrieval or CBIR. Systems using CBIR retrieve images based on visual features such as texture, color and shape, as opposed to depending on image descriptions or textual indexing. The main objective of this paper is to retrieve the images from database in a fast and an
efficient manner using modified Support vector method (SVM).

REFERENCES