RELEVANCE FEEDBACK FOR CONTENT BASED IMAGE RETRIEVAL BASED ON MULTITEXTON HISTOGRAM AND MICROSTRUCTURE DESCRIPTOR

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ABSTRACT
Image retrieval is an important topic in the field of pattern recognition and artificial intelligence. There are three categories of image retrieval methods: text-based, content-based and semantic-based. In CBIR, images are indexed by their visual content, such as color, texture, shapes. A new image feature detector and descriptor, namely the micro-structure descriptor [1] (MSD) is discussed to describe image features via micro-structures. The micro-structure is defined based on the edge orientation similarity, and the MSD is built based on the underlying colors in micro-structures with similar edge orientation. Content-based image retrieval (CBIR) is the mainstay of image retrieval systems. To be more profitable relevance feedback techniques are incorporated into CBIR such that more precise results can be obtained by taking user’s feedbacks into account. The semantic gap between low-level features and high-level concepts handled by the user is one of the main problems in image retrieval. On the other hand, the relevance feedback has been used on many CBIR systems such as an effective solution to reduce the semantic gap. The gap is reduced by using the Multitexton Histogram descriptor [2].

In this paper, a novel framework method called Relevance Feedback is used to achieve high efficiency and effectiveness of CBIR in coping with the large-scale image data. For that reason this paper proposes a method of relevance feedback based on Multitexton Histogram descriptor to represents the effective feature representations, and the Microstructure descriptor (MSD) for efficient feature extraction of an image. By using this method, high quality of image retrieval on Relevance Feedback can be achieved in a small number of feedbacks. In terms of efficiency, iteration of feedback is reduced substantially by using the navigation patterns discovered from the user query log, which reduce the computational processing time.

Keywords--- CBIR, Relevance Feedback, Semantic Gap, Microstructure descriptor (MSD), Multitexton Histogram descriptor.

I. INTRODUCTION
Images and graphics are among the most important media formats for human communication and they provide a rich amount of information for people to understand the world. In many areas of commerce, government, academia, and hospitals, large collections of digital images are being created. Many of these collections are the product of digitizing existing collections of analogue photographs, diagrams, drawings, paintings, and prints. Usually, the only way of searching these collections was by keyword indexing, or simply by browsing. Digital image databases however, open the way to content based searching. CBIR [3] system is required to help retrieve images based on visual properties such as color, texture or pictorial entities such as shape of an object. The primary goal of the CBIR system is to construct meaningful descriptions of physical attributes from images to facilitate efficient and effective retrieval. The primary goal of the CBIR system is to construct meaningful descriptions of physical attributes from images to facilitate efficient and effective retrieval.

In recent years, digital imaging has experienced tremendous growth in the world and it tends to increase exponentially. A way to retrieve this information is through the CBIR systems, although a large amount of research has been developed in this field, the performance in this system has not yet been successful due to the existence of semantic gap. Because of we use high-level concepts such as keywords or text descriptions to describe images content and/or to measure their similarity. While that the computer-vision systems can automatically extracted low-level features from images such as color, shape, texture and spatial relationships.

On the other hand there is also subjectivity of human perception of visual content of the images because of different persons or the same person under different circumstances, may perceive the same visual content differently during the information retrieval process [4], [5]. In that sense the CBIR systems try to reduce the semantic gap through relevance feedback based on the event activated human computer interaction model, which is a challenging task. The relevance feedback (RF), adapts the response of a system according to the relevant information fed back to it so that the adjusted response is a better approximation to the users information needs [6].

While there is much research effort addressing content-based image retrieval issues, the performance of content-based image retrieval methods are still limited, especially in the two aspects of retrieval accuracy and response...
time. The limited retrieval accuracy is because of the big gap between semantic concepts and low-level image features, which is the biggest problem in content-based image retrieval [7]. For a given query, the system first retrieves a list of ranked images according to predefined similarity metrics, which are often defined as the distance between feature vectors of images. In order to improve the retrieval accuracy of content-based image retrieval systems, research focus has been shifted from designing sophisticated low-level feature extraction algorithms to reducing the ‘semantic gap’ between the visual features and the richness of human semantics. The micro-structures are defined based on an edge orientation similarity, and the MSD [1] is built based on the underlying colors in microstructures with similar edge orientation. With microstructures serving as a bridge, the MSD extracts features by simulating human early visual processing and it effectively integrates color, texture and shape and color layout information as a whole for image retrieval.

In each iteration of the RF method, the system returns some images as the result for a query image and then the user evaluates the results according to his/her demands and preferences, and tells the system which images are relevant and which are irrelevant. The MTH is a new feature representation and descriptor to retrieval contend image which integrates the advantages of co-occurrence matrix and histogram by representing the attribute of co-occurrence matrix using histogram. The generation process of the tree is based on the results of similarity between images using the MTH descriptor, the assignment of weights and the user interaction. The rest of this paper is organized as follows. The related work is described in Section II. Section III deals with the proposed work which describes the relevance feedback approach for CBIR system, and finally section IV concludes the paper.

II. RELATED WORK

Guang-Hai Lieu et al. [1] proposed that human visual attention is enhanced through a process of competing interactions among neurons, which selects a few elements of attention and suppresses irrelevant materials. In order to extract features via simulating visual processing procedures and effectively integrate color, texture, shape features and im age color layout information as a whole for image retrieval, a novel feature detector and descriptor, namely microstructures descriptors (MSD). The MSD has advantages of both statistical and structural texture description approaches. In addition, the MSD algorithm simulates human visual perception mechanism to some extent.

Ja-Hwung et al. [8] described that conventional approaches for image retrieval are based on the computation of the similarity between the user’s query and images via a query by example (QBE) system. 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. To solve such problems, in the QBE system, the users can pick up some preferred images to refine the image explorations iteratively. The feedback procedure, called Relevance Feedback (RF), repeats until the user is satisfied with the retrieval results.

Marakakis et al. [9] introduced new relevance feedback (RF) approach for content-based image retrieval (CBIR), which uses Gaussian mixture (GM) models as image representations. The GM of each image is obtained as an adaptation of a universal GM which models the probability distribution of the features of the image database. In each RF round, the positive and negative examples provided by the user until the current round are used to train a support vector machine (SVM) to distinguish between the relevant and irrelevant images according to the preferences of the user.

Naresh Babu [10] showed that Content-based image retrieval (CBIR) is an important research area for manipulating large amount of image databases and archives. Extraction of invariant features is the basis of CBIR. The use HSI color information especially Hue value and CSS (Curvature Scale Space) as shape information. From a large image data base, an automatic shape & color Based retrieval technique can significantly increase the retrieval task. We are using three features for image retrieval like color, shape & texture Feature. As a Result Three Features combine fulfill the aspect of Retrieval in Image.

Jyothi et al. [3] proposed precise Relevance Feed Back (RFB) Content Based Image Retrieval (CBIR) using multiple features based on interactive retrieval approach which will extensively reduces the semantic gap between low-level features and high-level semantics. Relevance Feed Back improves the retrieval accuracy of Content Based Image Retrieval (CBIR) by modifying the query based on the user’s feedback in which the user can select the most relevant images and provide a weight of reference for each relevant image.

Lu Hui et. Al [11] introduces a relevance feedback system for CBIR with both short-term relevance feedback and long-term learning. In short-term relevance feedback, query reweighting algorithm, support vector machines (SVM), and genetic algorithm are adopted. In long-term learning, the expanded-judging model with index table is used for analyzing the historical log data. Through using the expanded judging model to analyze the historical feedback records, the system finds the semantic support to refine the similarity measure and improve the retrieval performance.
A simple and interactive method which shows effectiveness in natural image retrieval using relevance feedback through the generation of trees based on the Multitexton Histogram descriptor - MTH [2]. MTH descriptor analyzes the spatial correlation between neighboring color and edge orientation based on four special texton types. Because in the natural scenes the color and texture have close relationship in terms of fundamental elements and they are considered as atoms for pre-attentive human visual perception. RF confronts the subjectivity of humans in perceiving visual content and also eliminates the gap between high-level semantics and low-level features, which are often used for content description and modeling [13], [14]. Guang-Hai Liu et. al. [2] presented a novel image feature representation method, called multi-texton histogram (MTH), for image retrieval. MTH integrates the advantages of co-occurrence matrix and histogram by representing the attribute of co-occurrence matrix using histogram. The MTH method is based on Julesz’s textons theory, and it works directly on natural images as a shape descriptor. Meanwhile, it can be used as a color texture descriptor and leads to good performance. MTH can represent both the spatial correlation of texture orientation and texture color based on textons. MTH is well suited for large-scale image dataset retrieval. The natural scenes the color and texture have close relationship in terms of fundamental elements and they are considered as atoms for pre-attentive human visual perception [15]. Liu et. al [16], [17], [2] have demonstrated that MTH descriptor is much more efficient than representative image feature descriptors, such as the edge orientation autocorrelation and the texton co-occurrence matrix.

III. PROPOSED SYSTEM

Fig.1. shows the general scheme of the proposed system using relevance feedback in CBIR. The basic idea of relevance feedback is to shift the burden of finding the right query formulation from the user to the system.

Algorithm for proposed system is as follows:
Step1: Initially, user gives a query image and system provides images from the image database to the CBIR system. Then machine provides an initial retrieval results.
Step 2: In the next level of the system, identifies the feature representations of supplied images using the Multitexton Histogram (MTH) descriptor.
Step 3: Then applies the Microstructure descriptor on image to perform feature extraction on image.
Step 4: CBIR system is identifies the similarities (similarity measure) between the images.

Fig.1. Proposed Relevance Feedback system architecture

Step 5: system is retrieves the set of images for given query image on which user is going to give feedback in the way to find the relevant or irrelevant images (user required image).
Step 6: If the feedback is YES, then system retrieves user required image set. If NO, adjust the weights and return back to the Step 2.
Step 7: Repeat the steps from 2 to 6, until user gets relevant images.

The following sections describes in detail about important steps of proposed system. They are as follows:

3.1. RELEVANCE FEEDBACK

The Relevance Feedback is a technique that has been used quite successfully in human computer interaction; because of it allows users express better their needs in the specification of a query. In order to achieve this, after a user submits a query by a given sample, the system will return a set of similar images to the user. The returned images may not be fully relevant to the user’s targets. In order to learn the query concept of the user, relevance feedback is engaged as a query refinement technique for helping the retrieval task. The relevance feedback [30] mechanism solicits the user to mark the relevance on the retrieved images and then refines the results by learning the feedbacks from the user, at the same time that the system adjusts the low-level features of the images. The relevance feedback procedure is repeated again and again until the targets are found [18].

A typical scenario for relevance feedback in content-based image retrieval is as follows: [19]:

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i. Machine provides an initial retrieval results, through query-by-keyword, sketch, or example, etc.
ii. User provides a judgment on the currently displayed images as to whether, and to what degree, they are relevant or irrelevant to her/his request.
This process is illustrated in Fig.2.

![Fig.2. A typical Relevance Feedback process](image)

Within the traditional approach to relevance feedback are for example the method of the readjustment of weights of the feature query vector [14], where the user has to precisely decompose his information need into different feature representations and precisely specify all the weights associated with them, the proposed interactive approach allows the user to submit a coarse initial query and continuously refine his information need via relevance feedback.

Another classic approach is the query point movement method (QPM), which aggregates the positive examples as a new query point at each feedback. After several forceful changes of locations and contours, query point can be very close to a convex region of user’s interest [Su et al., 2011]. This method is based on the Rocchio’s formula which has been used in numerous applications [20], [21], [22].

Likewise, many systems based on relevance feedback assumes that the purpose of a query is to get a set of relevant image, which share similar features therefore also characterize to a class of similar images. In this sense the work presented by Zhang and Zhang [23] assumes the relevance feedback as a typical classification problem since it is natural that an indexed image data set can be classified into two classes of images, one is relevant in semantic content to the query and the other is irrelevant. So the authors have developed a novel approach, called BALAS, to empirical Bayesian learning to solve this classification problem. On the other hand, the goal of a CBIR system with relevance feedback can also be seen as a sorting problem [24], because the system retrieve the most relevant images in order of decreasing agreement, to relevance degree. Cheng et al. [25] propose a method applied to medical images, this method allows the user to define a ranking of relevance between images, which permit dynamically updates the weights of feature vector.

### 3.2. MULTITEXTON HISTOGRAM DESCRIPTOR (MTH)

Liu et al. [3] [17] presents a novel image feature representation method, called multitexton histogram (MTH), for image retrieval. MTH integrates the advantages of co-occurrence matrix and histogram by representing the attribute of co-occurrence matrix using histogram. It can be considered as a generalized visual attribute descriptor but without any image segmentation or model training. Multitexton histogram is suitable for natural image retrieval which represents the spatial correlation between neighboring color and edge orientation based on textons [12].

Natural scenes are usually rich in both color and texture, and a wide range of natural images can be considered as a mosaic of regions with different colors and textures [2]. For that reason in these natural scenes the Color and texture have close relationship in terms of fundamental elements and they are considered as atoms for pre-attentive human visual perception [12] [26] [15].

In this sense MTH represents an image by two matrices to analyze independently the spatial correlation between neighboring color and edge orientation based on four special texton types which are represented by four grids as shown in Fig. 3 (a). To each texton if the two pixels highlighted have the same value, then the grid will form a texton. Fig. 3 ((b), (c), (d) and (e)) shows the four special texton types of the proposed MTH.

![Fig.3. Four texton types (a) 2x2 grids, (b) T1, (c) T2, (d) T3, (e) T4](image)
The working mechanism of texton detection is illustrated in Fig.4. The 2x2 grids are moved from left-to-right and top-to-bottom throughout the edge orientation index image to detect textons with 2 pixels as the step-length. If a texton is detected, the original pixel values in the 2x2 grids are kept unchanged. Otherwise it will have zero value. Finally, the texton image is obtained, Fig. 4(e), which is used such as a mask to detect textons in the color index image.

In order to get the spatial correlation between neighboring color and edge orientation based on textons, MTH considers four orientations 0%, 90%, 45% and 135% with one of distance. Then to each orientation MTH forms a feature vector with 82 dimensions, where the first 64 dimensional vectors represent the spatial correlation between neighboring texture orientation by using color information and the last 18 dimensional vectors represent the spatial correlation between neighboring colors by using the texture orientation information. Finally, MTH descriptor calculates the average of the histograms to four different orientations. The Fig. 5 shows an example of an original image with this MTH descriptor.

![Fig. 4. Mechanism of texton detection to get the texton matrix](image)

3.3. MICRO-STRUCTURE DESCRIPTOR (MSD)

The contents in digital images can vary significantly so that directly comparing them is infeasible for applications such as image retrieval. However, the local structures of images from the same class (e.g. textile, mountains, etc.) often show a certain amount of similarity. The structural approach assumes that texture is formed with simple primitives called “texels” (texture elements) by following some placement rules. For example, the local binary pattern [27] can be considered as a type of texture elements. A typical example of “texels” is Julesz’s textons theory [28] [29], but it emphasizes on regular texture images. To address this problem, the concept of micro-structures is proposed in this paper for image retrieval. In some sense, we may think that the meaningful content of natural images is composed of many universal micro-structures. Therefore, if we could extract these micro-structures and describe them effectively, they can serve as common bases for the comparison and analyses of different images. This is the essential idea of this paper, and we call the proposed technique micro-structure descriptor (MSD).

3.3.1 Micro-Structured Image

Natural scenes are rich in color, texture and shape information and it can be considered as a mosaic of regions with different colors, textures and shapes. In general, textons are defined as a set of blobs or emergent patterns sharing a common property. Here, micro-structures are defined as the collection of certain underlying colors which have similar or the same edge orientation in uniform color space that combines color, texture and shape cues as a whole. In order to find the micro-structures, which have similar attributes such as edge orientation and color distribution, we partition the image into many small blocks, which can be a grid of size 2x2, 3x3, 5x5, 7x7 and so on. For the convenience of expression, the 3x3 block is used in the following development of microstructure analysis. In the 3x3 block, if one of the eight nearest neighbors has the same value as the center pixel, then it is kept unchanged; otherwise it is set to empty.

![Fig. 6. (a) Grid of edge orientation map; (b)–(c) show the microstructure detection process; and (d) shows the detected-fundamental micro-structure.](image)

3.3.2 Similarity Measure

Suppose there is an edge orientation map y(x,y) of size WxN. When we move the 3x3 block from left-to-right and top-to-bottom throughout the image, the detected fundamental microstructures in a neighborhood can overlap.
The following steps are used to obtain the micro structured image:
(1) Starting from the origin (0,0), we move the 3x3 block from left-to-right and top-to-bottom throughout the edge orientation image y(x,y) with a step-length of three pixels along both horizontal and vertical directions. Then, we will obtain a micro-structure map, denoted by M1(x,y), where 0<x<W-1, 0<y<N-1.
(2) Starting from the location (1,0), we move the 3x3 block from left-to-right and top-to-bottom with a step-length of three pixels along both horizontal and vertical directions. Then, a micro-structure map M2(x,y) is obtained, where 1<x<W-1, 0<y<N-1.
(3) Similarly starting from location (0,1), we can have the third micro-structure map M3(x,y), where 0<x<W-1, 1<y<N-1.
(4) Starting from location (1,1), we can have the fourth microstructure map M4(x,y), where 1<x<W-1, 1<y<N-1.
(5) The final micro-structure map, denoted by M(x,y), is obtained by fusing the four maps based on the following rule:
M(x,y) = Max{M1(x,y,M2(x,y),M3(x,y),M4(x,y)}

CONCLUSION
In this paper we proposed a new method to reduce the semantic gap by the relevance feedback image retrieval based on Multitexton Histogram descriptor. To deal with the long iteration problem of CBIR, can be reduced using Micro Structure Descriptor. In summary, the main feature of Relevance Feedback is to efficiently optimize the retrieval quality of interactive CBIR. Initially, the feature representation done with Multitexton Histogram, then generated micro structured image is used in retrieving images from the database. Later, from the retrieved image user feedback is given for a pattern-based search to match the user’s intention. Finally the most relevant set of images are retrieved from the database. As a result, traditional problems such as visual diversity and exploration convergence are solved.

REFERENCES
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