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Content Based Image Retrieval Using Color and Texture Feature with Efficient Relevance Feedback

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Abstract---- The purpose of CBIR is to present an image conceptually, with a set of low-level visual features such as color, texture, and shape. The computational complexity and the retrieval accuracy are the main problems in CBIR. To avoid these problems, the proposed system proposes a new content-based image retrieval method that uses both color and texture feature. For the color feature color moment method is used and for texture feature Completed Local Binary Pattern(CLBP) method is used. Relevance feedback techniques were incorporated into CBIR such that more precise results can be obtained by taking user's feedbacks into account. Existing relevance feedback-based CBIR methods usually request a number of iterative feedbacks to produce refined search results, especially in a large-scale image database. So the proposed system uses Navigation-Pattern-Log-based Relevance Feedback (NPLBRF) to achieve the high retrieval quality of CBIR with RF by using the discovered navigation patterns. The discovered navigation pattern is stored in log database. By using NPLBRF method, high quality of image retrieval on RF can be achieved in a small number of feedbacks. Also in the proposed system, the feature space is decomposed according to the user interest.

Keyword— CBIR, LBP, RF, NPLBRF

I. INTRODUCTION

Content Based Image Retrieval (CBIR) is the retrieval of mages based on their visual features such as color, texture, and shape. Content-based image retrieval systems have become a reliable tool for many image database applications. A typical CBIR uses the contents of an image to represent and access. CBIR systems extract features (color, texture, and shape) from images in the database based on the value of the image pixels. These features are smaller than the image size and stored in a database called feature database. Thus the feature database contains an abstraction (compact form) of the images in the image database; each image is represented by a compact representation of its contents (color, texture, shape, and spatial information). The main advantage of using CBIR system is that the system uses image features which is stored in feature database instead of using the image itself. So, CBIR is cheap, fast, and efficient over image search methods [1].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 multiple visual characteristics [1].It also gives poor result. The proposed system uses color and texture features from the image. For the color feature, color moment feature method is used and mean and standard deviation color moment is calculated. For texture feature Completed Local Binary Pattern (CLBP) method is used. In general, the purpose of CBIR is to present an image conceptually, with a set of low-level visual features such as color, texture, and shape. These 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 [2]. The feedback procedure, called Relevance Feedback (RF), repeats until the user is satisfied with the retrieval results. Existing relevance feedback-based CBIR methods usually request a number of iterative feedbacks to produce refined search results, especially in a large-scale image database. This is impractical and inefficient in real applications. The proposed system will use a novel method named Navigation-Pattern-Log-Based Relevance Feedback (NPLBRF)to achieve the high retrieval quality of CBIR with RF by using the discovered navigation patterns. The navigation patterns mined from the user query log can be viewed as the shortest paths to the user's interested space. According to the discovered patterns, the users can obtain a set of relevant images.

II. STRUCTURE OF PROPOSED CBIR SYSTEM

A CBIR system can collect and store user's relevance feedback information in a log database. An image retrieval system should take advantage of the log data of user's feedback to enhance its retrieval performance. A log-based relevance feedback is a technique that integrates the log of feedback data into the traditional relevance feedback schemes to learn effectively the correlation between low-level image features and high-level concepts[6]. This method computes the relevance information between query images and images in the database using both the log data and the low-level features of images and combine them to produce a more accurate estimation of relevance score.

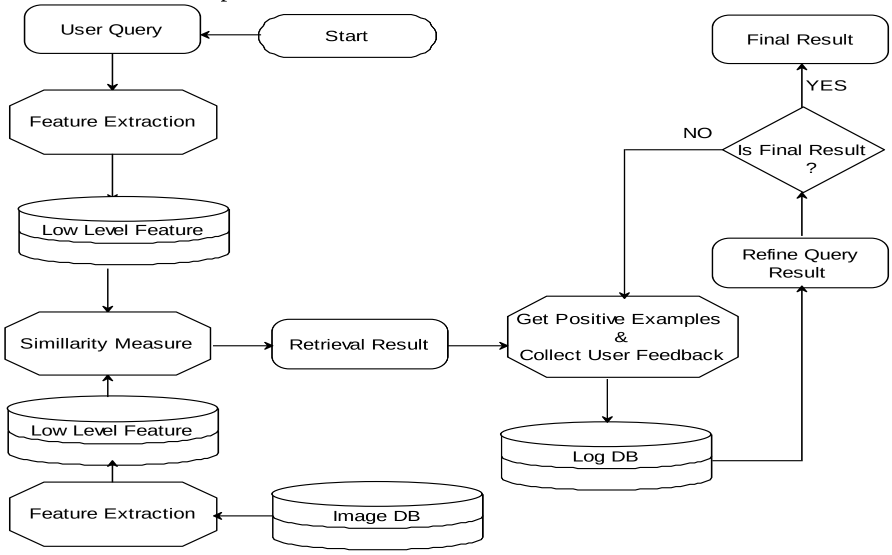

Fig 1 Architecture of Proposed System

As shown in Figure 1,in the proposed system relevance feedback from users is collected and stored in a log database. When feedback log data is unavailable, this system behaves exactly like a regular relevance feedback algorithm, which learns the correlation between low-level features and users information needs through the feedback image examples. When feedback log data is available, the system will learn such a correlation using both the feedback log data and the feedback from users. The log-based relevance feedback scheme is able to achieve the retrieval goal in only a few iterations with the help of the log data of user's feedback. Thus, the proposed system display the relevant images from database as well as the images that is retrieved by previous user for that query image.

A. Extract Color Feature

Color features are the fundamental characteristics of the content of images[1]. Color feature is one of the most widely used features in low level feature. Compared with shape feature and texture feature, color feature shows better stability and is more insensitive to the rotation and zoom of image. Color not only adds beauty to objects but also more information, which is used as powerful tool in content-based image retrieval.

1) Color Moment:

Color moments are scaling and rotation invariant. Any color distribution can be characterized by its moments and most information is concentrated on the low-order moments, only the first moment (mean), the second moment (variance) are taken as the feature vectors. The similarity between two color moments is measured by any similarity method. Two similar images will have high similarity. However, if two images have only a similar sub-region, their corresponding moments will be different and the similarity measure will be low.

To extract the color features from the content of an image, we need to select a color space and use its properties in the extraction. In common, colors are defined in three-dimensional color space. Color moments can be computed for any color model. Two color moments are computed per channel. In digital image purposes, RGB color space is the most prevalent choice. This color system is very useful in interactive color selection and manipulation [1]. The first-order (mean), the second (standard deviation) color moments have been proved to be efficient and effective in representing color distributions of images.

Moment 1: Mean

The first color moment can be interpreted as the average color in the image, and it can be calculated by using the following formula:

$$Ei = \frac{1}{N}\sum_{j=1}^{N} \mathrm{Pij}$$

P_{ij} is the color value of the *i*-th color component of the *j*-th image pixel and *N* is the total number of pixels in the image.

Moment 2: Standard Deviation

The second color moment is the standard deviation, which is obtained by taking the square root of the variance of the color distribution. It can be calculated using following formula:

$$\sigma\mathrm{i} = \sqrt[2]{\frac{1}{N}\sum_{j=1}^{N}(\mathrm{Pij} - \mathrm{Ei})^2}$$

where E_i is the mean value, or first color moment, for the i-th color channel of the image.

B. Extract Texture Feature

Texture provides the measures of properties such as smoothness, coarseness, and regularity. Furthermore, texture can be thought as repeated patterns of pixels[1]. Texture is an innate property of all surfaces that describes visual patterns, each having homogeneity. It contains important information about the structural arrangement of a surface, such as; clouds, leaves, bricks, fabric, etc. It also describes the relationship between the surfaces to the surrounding environment. In short it is a feature that describes the distinctive physical composition of a surface. To extract the texture feature, Completed Local Binary Pattern (CLBP) is found to be a powerful feature.

[1] Completed Lbp (Clbp):

- Local Difference Sign-Magnitude Transform

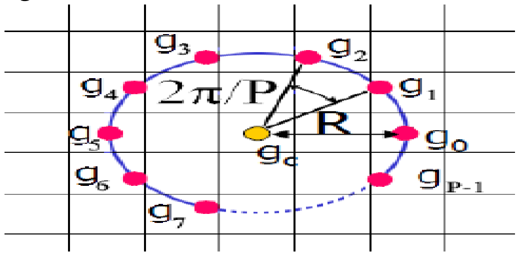

Fig 2 Central pixel and its *P* circularly and evenly spaced neighbours

9	12	34
10	25	28
99	64	56

(a)

-16	-13	9
-15		3
74	39	31

(b)

-1	-1	1
-1		1
1	1	1

(c)

16	13	9
15		3
74	39	31

(d)

Fig 3 (a) A 3X3 sample block; (b) the local differences; (c) the sign and (d) magnitude components.

Referring to Fig. 4.1, given a central pixel *c g* and its *P* circularly and evenly spaced neighbours *p g* , *p*=0,1,…,*P*-1, we can simply calculate the difference between *c g* and *p g* as *p p c d g g* . The local difference vector 0 1 ,..., *P d* characterizes the image local structure at *c g* . Because the central gray level *c g* is removed, 0 1 ,..., *P d* is robust to illumination changes and they are more efficient than the original image in pattern matching. *p d* can be further decomposed into two components:

$$d_p=s_p*m_p \text{ and } \begin{cases} s_p=\text{sign}(d_p) \\ m_p=|d_p| \end{cases} \qquad (1)$$

where $S_p=\begin{cases}1, d_p\geq 0\\ -1, d_p<0\end{cases}$ is the sign of *dp* and m_p is the magnitude of *dp* . With Eq. (1), [d_0,……, d_{p-1}] is transformed into a sign vector [$s0,\ldots,s_{p-1}$] and a magnitude vector [m_0,…. ,m_{p-1}].

We call Eq. (1) the local difference sign-magnitude transform (LDSMT). Obviously, [$s0,\ldots,s_{p-1}$] and [m_0,…. ,m_{p-1}] are complementary and the original difference vector [d_0,……, d_{p-1}] can be perfectly reconstructed from them. Fig. 4.6 shows an example. Fig. a is the original 3 x 3 local structure with central pixel being 25. The difference vector (Fig. b) is [3, 9,-13,-16,-15, 74, 39, 31]. After LDSMT, the sign vector (Fig. 2c) is [1,1,-1,-1,-1,1,1,1] and the magnitude vector (Fig. 4.2d) is [3, 9, 13, 16, 15, 74, 39, 31]. It is clearly seen that the original LBP uses only the sign vector to code the local pattern as an 8-bit string "11000111" ("-1" is coded as "0").

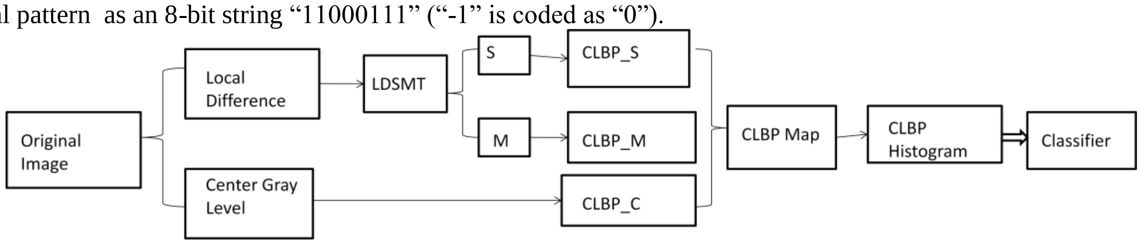

Fig 4 Framework of CLBP

- Analysis on Sign & Magnitude Components

Vector [d0,….., dp-1]characterizes the image local structure. However, texture recognition by direct matching [d0,….., dp-1] is infeasible because it is sensitive to noise, translation and rotation, etc. Thus we need to extract the distinct and stable features from [d0,….., dp-1]to robustly recognize texture patterns. In Section A, we have seen that LBP actually uses only the sign component of [d0,….., dp-1]for pattern recognition. Apparently, this may lead to some incorrect matches. For example, the difference vectors [3, 9, -13, -16, -15, 74, 39, 31] and [150, 1, -150, -1, -100, 150, 1,150] have the same sign vector [-1,-1,-1,1,1,1,1,1]. However , it is hard to say they have similar local structures[20].

Therefore, several issues need to be addressed for LBP based feature representation. First, why LBP works reasonably well by using only the sign components of the local difference vector? Second, how to exploit the remaining information existed in the magnitude component? Third, can we design a scheme to efficiently and conveniently fuse the sign- magnitude features?

The local difference can be perfectly reconstructed from its sign-magnitude components by $dp=sp*mp$. One intuitive question is that which component, sp or mp, is more informative to represent the original local difference dp? From a viewpoint of signal reconstruction, we can answer this question by reconstructing dp using only sp or mp, and then checking which component can yield a smaller reconstruction error. Since dp is the multiplication of sp and mp, we cannot directly reconstruct dp by leaving one of sp and mp out.

- *CLBP_S, CLBP_M, and CLBP_C Operators*

In Sub-section B, we illustrated that the sign component preserves much the information of local difference. This explains why the simple LBP technique can reasonably represent the image local features. Meanwhile, we see that the magnitude component may contribute additional discriminate information if it is properly used. In addition, the intensity value of the center pixel itself can also contribute useful information [3]. In this sub-section, we present a completed LBP (CLBP) framework to explore all the three types of features. The CLBP framework is illustrated in Fig. 4.7.

1. We first represent the original image as its center gray level (C) and the local difference.
2. The local difference is then decomposed into the sign (S) and magnitude (M) components by the LDSMT defined in Eq. (1).
3. Consequently, three operators, namely CLBP_C, CLBP_S and CLBP_M, are proposed to code the C, S and M features, respectively.
4. Then, the CLBP_C, CLBP_S and CLBP_M codes are combined to form the CLBP feature map of the original image.
5. Finally, a CLBP histogram can be built, and some classifier, such as the nearest neighbourhood classifier, can be used for texture classification.

The CLBP_S operator is the same as the original LBP operator . Since the M components are of continuous values instead of the binary "1" and "-1" values, they cannot be directly coded as that of S.

C. Relevance Feedback

Relevance feedback is a technique that takes advantage human-computer interaction to refine high level queries represented by low level features. It is used in traditional image retrieval using information fed back from the user. In the application of image retrieval**,** the user selects relevant images from previous retrieved results and provides a preference weight for each relevant image[4]. Based on the feedback, the high level concepts implied by the feature weights and relevant feedbacks are automatically refined. During the process of relevant feedback, the similarity between the query and the images in the database are calculated[4].

Relevance feedback as afore cited fulfill an important role in CBIR systems, due to its ability to gradually reduce the semantic gap through users interactions[9]. Basically, a relevance feedback technique is composed of three steps in CBIR: (1) the system retrieves the most similar images according to the initial query; (2) the user guide the search process, judging the returned images based on a degree of relevance (e.g. relevant or irrelevant) in comparison to the query; (3) the system capture the user's expectation retrieves the most relevant images based on the performed feedback. Then, steps (2) and (3) are repeated until the user is satisfied with the results[5].

Although a number of RF studies have been made on interactive CBIR, they still incur some common problems, most existing RF methods focus on how to earn the user's satisfaction in one query process. That is, existing methods refine the query again and again by analyzing the specific relevant images picked up by the users. Especially for the compound and complex images, the users might go through a long series of feedbacks to obtain the desired images using current RF approaches. In fact, it is not practical in real applications. Existing relevance feedback-based CBIR methods usually request a number of iterative feedbacks to produce refined search results, especially in a large-scale image database. This is impractical in real applications. The proposed system will use a novel method named Navigation-Pattern-Log-based Relevance Feedback (NPLBRF) to achieve the high retrieval quality of CBIR with RF by using the discovered navigation patterns. The navigation patterns mined from the user query log can be viewed as the shortest paths to the user's interested space. It gives the result in few number of iteration.

D. Similarity Measure

One fundamental step in CBIR system is the similarity measures. Check the similarity between query image and image in the database.Similarity between two images is to find the distance between them. The distance between two images can be calculated using feature vectors that are extracted from the images. Therefore, the retrieval result is not a single image, but many images will be retrieved similar to the input image[1]. Different similarity measures have been proposed based on the distribution of features, so the kind of features extracted from the image and the arrangement of these features in a vector will determine the kind of similarity measures to be used. Different similarity measures will affect the retrieval performance of image retrieval significantly.

In this system I am using the chi-square distance Measure. Chi-square Distance is used to measure the similarity between two images with N-dimensional feature vector. Suppose we have two feature vectors X and Y such that *X* = (x0, x1, …,xN-1) and *Y* = (y0, y1, …, yN-1). The chi-square Distance between X and Y will be:

$$\mathrm{dchi}(\mathrm{x},\mathrm{y}) = \sum_{i=1}^{d} \frac{(xi - yi)^2}{xi + yi}$$

III. IMPLEMENTATION AND RESULT

A. Proposed Algorithm

Purpose: The algorithm is to retrieve images similar to the query image.
Input: An RGB image, number of retrieved images n.
Output: n images similar to the input image.

1) Extract Color Feature:

1.Take the query image as well as image in the database which is RGB color space
2. Calculate the color moments that is Mean and Standard Deviation for each image using equations.
3. Construct the color feature vector that is a 6 dimension vector.

2) Extract Texture Feature:

1. Take the query image as well as image in the database.
2. Generate CLBP features
   a. Generate histogram of CLBP_S
   b. Generate histogram of CLBP_M
   c. Generate histogram of CLBP_C
3. Retrieval test using CLBP_S, original LBP
   a. compute the distribution of Training and test data using CLBP_S histogram, Original LBP

3) Similarity Measure:

1. Find the chi-square distance between training and test distribution
2. Using Nearest Neighbor Classifier find the top 20 images which is similar to test image.

4. Navigation Pattern Log Based Relevance Feedback:

1. Take a query image.
2. Extract color and texture feature from the image.
3. Find the matching images from image database.
4. Get the positive examples.
5. Refine query result.Display the relevant images from database as well as the images that is retrieved by previous user for that query image.
6. Find the top relevant images.
7. Collect feedback from user.
8. If user is not satisfied then repeat the steps.If user is satisfied then Stop and return the retrieval result to user.

B. Results

I choose the database provided by James S. Wang for testing the proposed method. WANG [7] database is an image database where the images are manually selected from the Corel database. In WANG database, the images are divided into 10 classes. Each class contains 100 images. It is widely used for testing CBIR systems. Classification of the images in the database into 10 classes makes the evaluation of the system easy.For evaluation, I use all the images in the database. Each image in the database went through the proposed method to extract the color feature and the texture feature. The image retrieval system is implemented using MATLAB image processing tools.

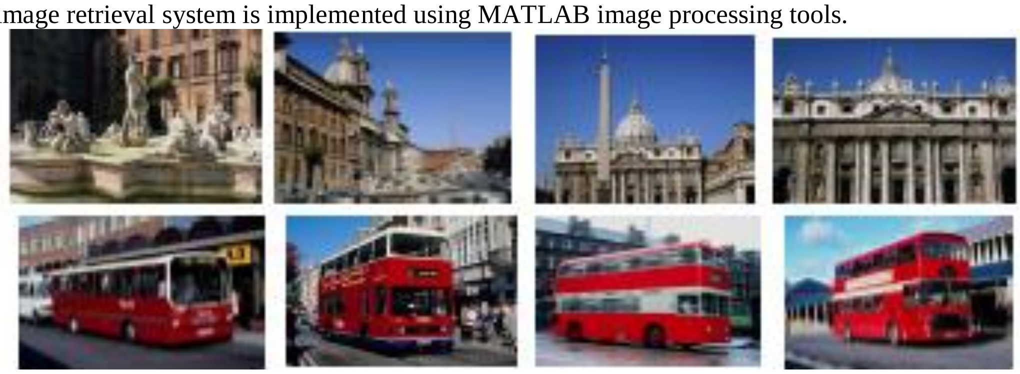

Fig.5 Sample WANG Database

To evaluate a CBIR system, it is necessary to choose some performance measure. The problem is that neither a standard image database nor a unique performance measure is available. There are many image databases that are used to represent results for Content Based Image Retrieval system(CBIR) system. So, no standard image database are available for CBIR systems. Therefore, it is impossible to compare the performance of different systems using different image databases.

In CBIR, the most commonly used performance measures are Precision . Precision is defined as the ratio of the number of relevant images retrieved to the total number of retrieved images . Precision is denoted by P. The equation of Precision is:

$$\mathrm{P} = \frac{\text{Number of relevant image retrieved}}{\text{Total number of images retrieved}}$$

In CBIR, if the precision score is 1.0, this means that every image retrieved by a search is relevant.

Table I. Retrieval rate for types of images

Sample Image	**0RF**	**1RF**
Buildings	60%	90%
Buses	40%	80%
Elephants	45%	65%
Flowers	65%	90%
Horses	60%	75%
Mountains	40%	60%
Foods	60%	80%

Table II shows the precision of the existing system and the proposed system.The proposed system is compared with[1] and [8]

Table II. Evaluation of the existing system and proposed system

Semantic Groups	CMR	CMW+GTF	CMR+GTF	Proposed system
Buildings	0.8	0.30	0.36	0.9
Buses	0.7	0.60	0.77	0.8
Elephants	0.5	0.58	0.44	0.65
Flowers	0.7	0.71	0.69	0.9
Horses	0.5	0.47	0.67	0.75
Mountains	0.5	0.36	0.41	0.6
Foods	0.4	0.72	0.69	0.8

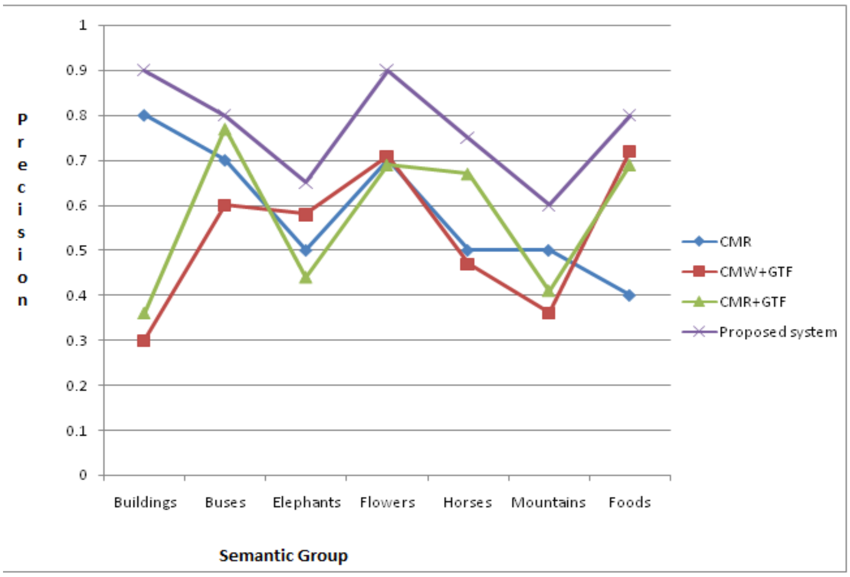

Fig 6 Performance comparison of existing system and proposed system

IV. CONCLUSION

The purpose of CBIR is to present an image conceptually, with a set of low-level visual features such as color, texture, and shape. The computational complexity and the retrieval accuracy are the main problems in CBIR. To avoid these problems, the proposed system uses both color and texture feature . CBIR gives more accurate result with multiple feature than with a single feature Relevance feedback techniques were incorporated into CBIR such that more precise results can be obtained by taking user's feedbacks into account. Existing relevance feedback-based CBIR methods usually request a number of iterative feedbacks to produce refined search results. So the proposed system uses Navigation-Pattern-based Relevance Feedback to achieve the high retrieval quality of CBIR with RF by using the discovered navigation patterns. Also in the proposed system, the feature space is decomposed according to the user interest.

In the future, I will try to make this system online. Also try to test this system on other image database. This system will add the shape feature along with color and texture feature.

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