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Mining in Navigation-Pattern using Content-Based Image Retrieval

K. Karthika, C. Arunachal Aperumal

***Abstract:** Research has been devoted in the past few years to relevance Feedback as an effective solution to improve performance of Content-based image retrieval (CBIR). In this paper, we propose a color image pattern for further use, which reduce the iteration og image. To achieve the high efficiency and effectiveness of CBIR we are using two type of methods for feature extraction like SVM (support vector machine) and NPRF (navigation-pattern based relevance feedback).By using svm classifier as a category predictor of query and database images, they are exploited at first to filter out irrelevant images by its different low-level, concept and key point-based features. Thus we may reduce the size of query search in the db and enhanced by using texture based in which we combine GLCM and CCM.*

***Index Terms:** GLCM, CCM, SVM, contentbased image retrieval.*

I. INTRODUCTION

CONTENT-BASED image retrieval (CBIR) is a process to find images similar in visual content to a given query from an image database. It is usually performed based on a comparison of low level features, such as color, texture or shape features, extracted from the images themselves. 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. For example, for different queries, different types of features have different significance; an issue is how to derive a weighting scheme to balance the relative importance of different feature type and there is no universal formula for all queries.Content-Based Image Retrieval (CBIR) is the mainstay of current image retrieval systems. 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 [11]. 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.

The rest of the paper is organized as follows: A review of past studies is briefly described in Section 2. In Section 3, we describe the details of our proposed method. Empirical evaluations of the proposed method are expressed in Section 4. Finally, we conclude the paper in Section 5.

II. PRIOR AND RELATED WORK

Relevance feedback [5], [2], [12], in principle, refers to a set of approaches learning from an assortment of users' browsing behaviors on image retrieval [10]. Some earlier studies for RF make use of existing machine learning techniques to achieve semantic image retrieval, including Statistics, EM, KNN, etc. Although these forerunners were devoted to formulating the special semantic features for image retrieval, e.g., Photobook [11], QBIC [1], VisualSEEK [16], there still have not been perfect descriptions for semantic features. This is because of the diversity of visual features, which widely exists in real applications of image retrieval. Therefore, active query refinement, based on the analysis of usage logs, attracts researchers' attention in this area of RF.

It is very difficult to derive an adaptive and perfect measuring function. A specific measuring function indeed cannot cover all target groups with various visual contents. Moreover, the modified query point of each feedback probably moves toward the local optimal centroid. Thus, global optimal results are not easily touched in QPMlike work spreading in the broad feature space. As a result, diverse results for the same concept are difficult to obtain. For this reason, the modified version of MARS [9] groups the similar relevant points into several clusters, and selects good representative points from these clusters to construct the multipoint query.

One of the hybrid RF strategies is IRRL. IRRL, proposed by Yin et al. [18]

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* Correspondence Author
K.Karthika (M.E), Dept. of PG Studies &Engineering, S.A Engineering college, Anna University of Technology, Chennai India.
C. Arunachalaperumal, M.E PhD, Dept. of PG Studies & Engineering, S.A Engineering college, Anna University of Technology, Chennai India.

addresses the important empirical question of how to precisely capture the user's interest at each feedback. In IRRL, exploiting knowledge from the long-term experience of users can facilitate the selection of multiple RF techniques to get the best results. The derived problems from IRRL are: the selection of optimal RF technique cannot avoid the overhead of long iterations of feedback. Also, the visual diversity existing in the global feature space cannot be resolved with an optimal RF technique alone.

NST Sai, et.al [3] , describes two approaches to content based image retrieval (CBIR) that represent each image in database by a vector of feature values. It applies DCT on average value of row and column vector and DCT on pixel distribution of row and column vector. Feature vector each image is DCT coefficients. The drawback is it does not display the images in ranked manner. It considers only the color features, so scale orientation is not possible in this method.

III. PROPOSED SYSTEM

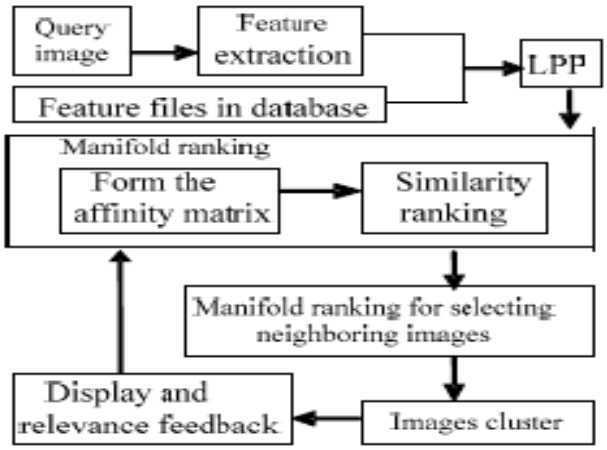

Fig 1.Navigation Patterns Based On The Graph Partitioning For Modeling

Fig.1 gives the overview of the proposed method CNPM (Combined Navigation Pattern Mining) with Relevance Feedback where both the color and texture features are combined to yield better iterative results. It consists of four modules modules: Navigation Pattern Mining, Color Based Image Retrieval ,Texture Based Image Retrieval and Relevance Feedback.

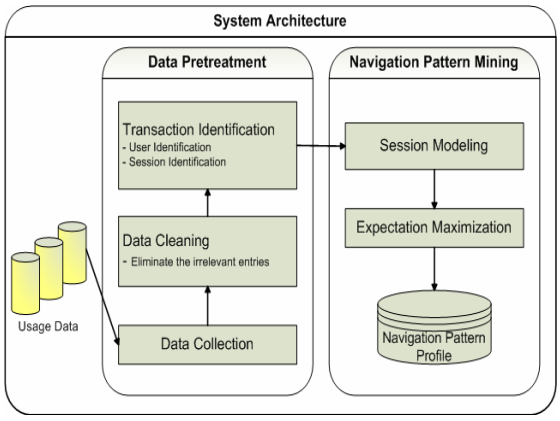

Fig **2.Navigation Pattern Mining**

(a) Navigation Pattern Mining

The main objective of this module is mining of user's navigation pattern. A user navigation pattern is common browsing characteristics among a group of users. Since many users may have common interests up to a point during their navigation, navigation patterns should capture the overlapping interests or the information needs of these users. In addition, navigation patterns should also be capable to distinguish among web pages based on their different significance to each pattern. The large majority of methods that have been used for navigation pattern mining from Web data are clustering methods. Clustering aims to divide a data set into groups that are very different from each other and whose members are

Very similar to each other.

Query point generation. The basic idea of this operation is to find the images not only with the specific similarity function. By recursively modifying the query point, the search direction can move toward the targets gradually. Assume that a set of images is found by the query point at the preceding feedback. Next, the visual features of the positive examples G picked up by the user are first averaged into a new query point.

(b) Color Based Image Retrieval:

Color is the first and most straightforward visual feature for indexing and retrieval of images (Swain and Ballard, relatively robust and simple to represent. It is also the most commonly used feature in the field. Color has been an active area of research in image retrieval, more than in any other branch of computer vision. Color makes the image take values in a color vector space.

The choice of a color system is of great importance for the purpose of proper image retrieval. An important criterion is that the color system is independent of the underlying imaging device. This is required when images in the image database are recorded by different imaging devices such as scanners, camera's and cam recorder (e.g. images on Internet). Another prerequisite might be that the color system should exhibit perceptual uniformity meaning that numerical distances within the color space can be related to human perceptual differences. This is important when images are to be retrieved which should

be visually similar (e.g. stamps, trademarks and paintings databases).

(c) Texture Based Image Retrieval:

Texture based image retrieval is characterised by three steps. First, for each image in the image collection, a feature vector of size ten, characterizing texture of the image is computed based on the Wavelet transformation method. The Wavelet transformations are used because they capture the local level texture features quite efficiently, where feature vectors are stored in a feature database.

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Second, using clustering algorithm to construct indexed image database based on the texture feature vectors obtained from wavelet transformation, and finally, given a query image, its feature vector is computed and compared to the feature vectors in the feature database, and relevant images to the query image from the image database returned to the user[17]. Every care has been taken to ensure that the features and the similarity measure used to compare two feature vectors are efficient enough to match similar images and to discriminate dissimilar ones. The main aim of this approach is that not even a single relevant image should be missed in the output as well as to minimize the number of irrelevant images.

(d) Relevance Feedback:

Relevance feedback approach In the proposed relevance feedback approach, positive and negative feedback examples are incorporated in the query refinement process with different strategies. To incorporate positive feedback in refining image retrieval, we assume that all of the positive examples in a feedback iteration belong to the same semantic class whose features follow a Gaussian distribution. Features of all positive examples are used to calculate and update the parameters of its corresponding semantic Gaussian class and we use a Bayesian classifier to re-rank the images in the database. To incorporate negative feedback examples, we apply a penalty function in calculating the final ranking of an image to the query image. That is, if an image is similar to a negative example, its rank will be lowed depending on the degree of the similarity to the negative example.

Iv. Experimental results

In this section, a selection of experimental results is presented to demonstrate the effectiveness of the proposed approach. The performance of the system was assessed in terms of precision (number of retrieved relevant images over) and recalls (percentage of relevant images retrieved across all iterations with respect to the number of class samples). The precision-recall curves are calculated after all the iterations. All the precision-recall curves are calculated considering the ranked images. MATLAB is used to evaluate the proposed scheme. Dataset of about 70 images are taken and computation time for retrieval is analyzed for both color and texture Based retrieval system. Results and its retrieval accuracy are analyzed for various distant measures.

The performance of image retrieval is measured using: two major criteria, namely precision and recall are used to measure the related experimental evaluations. They are defined as follows,

$$\text{Precision} = \frac{\text{number of correct documents retrieved}}{\text{number of total documents retrieved}} \quad (1)$$

$$\text{Recall} = \frac{\text{number of correct documents retrieved}}{\text{number of total documents in relavant class}} \quad (2)$$

Simulation result:

This simulation result shows, the calculation of matrix value as shown in fig 3

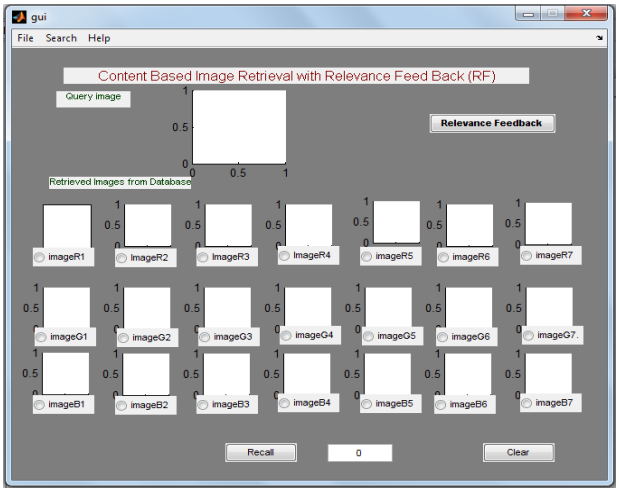

Fig 3: Matrix calculation

This simulation result shows, the matrix value only if it match with previous result. If it is not matched result won't be displayed.

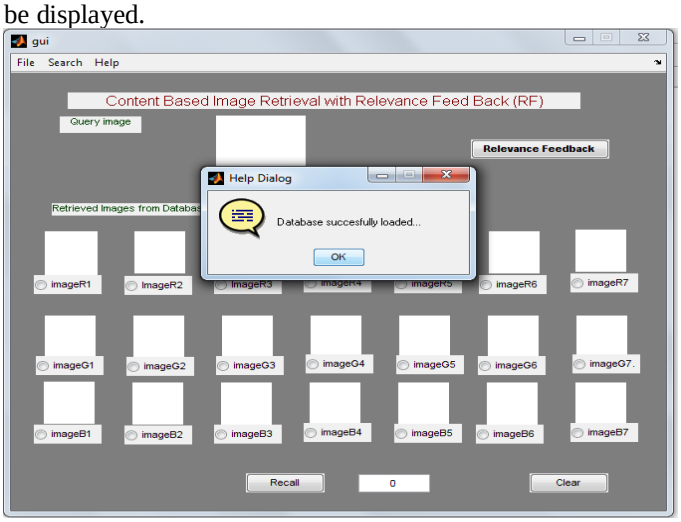

Fig 4: Matrix process comparation

This simulation result shows, first it gives the query and search for relevant information.

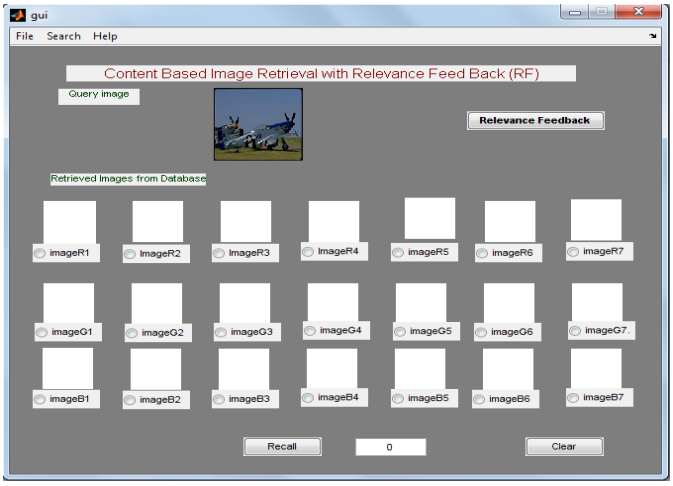

Fig 5: Loading query database

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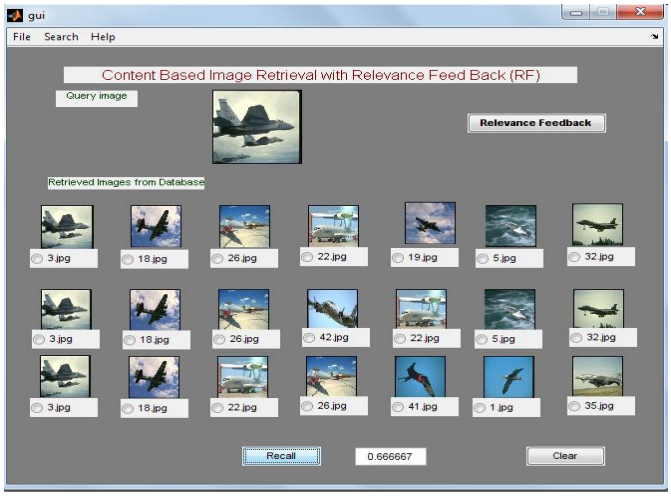

Fig 6: Relevant image Retrieval

Fig.4 and Fig.5 shows the association between average recall and precision values on CNPM based image set values. Recall value increases as the number of returned images increases.

V. CONCLUSION AND FUTURE WORK

This paper describes the new image retrieval system named Combined Navigation Pattern Mining (CNPM) where both combinations of color and texture features are taken to achieve the high efficiency and effectiveness of CBIR in coping with the large-scale image data using Navigation-Pattern with Relevance Feedback .The proposed system refines the retrieved images to narrow down the images. The performance of our approach has been demonstrated for a bag-of-features-based image search system. A large set of experiments shows that the accuracy is significantly and consistently improved by the CDM for two different data sets. It also analyzes several variants and the impact of the main parameters of our image search system. Our final system significantly outperforms the state of the art on both data sets

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