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Semi Supervised Collaborative Image Retrieval Using Binary Classifier.

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Abstract- **Content Based Image Retrieval (CBIR) is commonly used in image processing. But the accuracy of CBIR system is not very high. To improve the performance of CBIR system Relevance feedback system can be used. In relevance feedback system the user refines the search results progressively by marking images in the results as "relevant", "irrelevant", or "neutral" to the search query and then repeating the search with the new information. In many cases there may be large number of images to label. Most of the times user would not like to label a large number of images. So in this paper we are using semi-supervised method. This means the user needs to label only few most informative images. These labeled images are then used as training set for SVM classifier. Then images in database are resorted based on new similarity metric. If the user is satisfied with the results, Relevance feedback is no longer required and the system gives the final results. These results are most semantically relevant to the query image. Thus the image retrieval process is ended. Otherwise, Relevance Feedback will be performed iteratively.**

Key Words- **Content Based Image Retrieval(CBIR), Semantic Gap, Relevance Feedback(RF), Feature Selection, Binary Classifier, Precision, Recall.**

I. INTRODUCTION

Content Based Image Retrieval(CBIR) has gained much popularity . It is commonly used in image processing. In Content-based image retrieval visual contents are used to search images from large scale image databases according to user interest. But one of the reasons for poor performance of CBIR is the gap between low level and high level features. Also users viewpoint for same image may be different at different times. Also in CBIR, images with same visual features but different semantics may be considered as identical. This problem is called as semantic gap.

Now to solve these problems relevance feedback can be used. In relevance feedback system the user progressively refines the search results by marking images in the results as "relevant", "irrelevant", or "neutral" to the search query and then repeating the search with the new information. In many cases there may be large number of images to label. Most of the times user would not like to label a large number of images. So in this paper we are using semi-supervised method. This means the user needs to label only few most informative images. These labeled images are then used as training set for SVM classifier. Then images in database are resorted based on new similarity metric. If the user is satisfied with the results, Relevance feedback is no longer required and the system gives the final results. These results are most semantically relevant to the query image. Thus the image retrieval process is ended. Otherwise, Relevance Feedback will be performed iteratively. This improves the performance of CBIR system.

II. CONTENT-BASED IMAGE RETRIEVAL (CBIR)

Content-based image retrieval (CBIR), also known as Query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem. Thus it is the problem of searching for digital images in large databases. Content-based image retrieval contrasts with traditional concept-based approaches."Content-based" means that on searching, the contents of the image are analysed rather than the metadata such as t keywords, descriptions or tags associated with the image according to process as shown in Fig. 1.

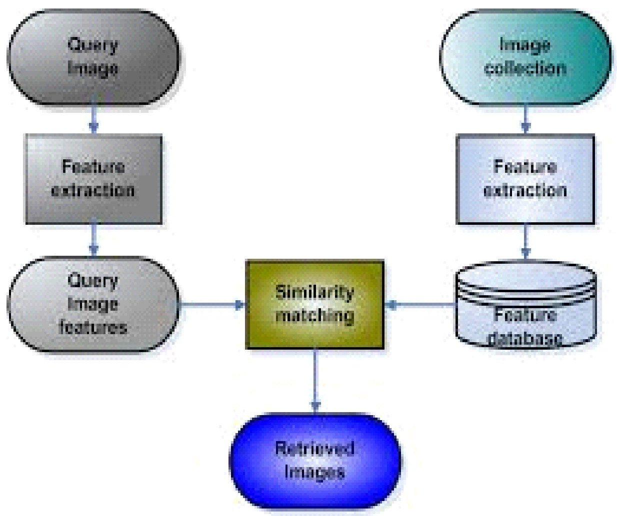

Fig. 1 Working Principle of CBIR.

The term "content" in this context might refer to shapes, colours, textures, or any other information that can be derived from the image itself. The searches that rely purely on metadata are dependent on annotation quality and completeness. Hence CBIR is desirable. Making humans manually annotate images by entering keywords or metadata in a large database can be time consuming and may not capture the keywords required to describe the image. The evaluation of the effectiveness of keyword image search is subjective and has not been well-defined. In the similar context, CBIR systems have similar challenges in defining success.

Two main problems faced by CBIR systems are:

a) Production of low level image features that accurately describe human visual perception.

b) Computational complexity: The high dimensional feature vector gives better information about the image content. It increases the computational complexity when working with high dimensional vectors. Thus CBIR suffers with „curse of dimensionality".

C) semantic gap: One of the reasons for poor performance of CBIR is the gap between low level and high level features. Also users viewpoint for same image may be different at different times. Also in CBIR, images with same visual features but different semantics may be considered as identical. This problem is called as semantic gap.

An example for semantic gap is shown in fig. 2.For query image on left side of fig. 2, some users may focus on the sea beach so the best match can be a sea beach like the one in the middle image; while others may focus on the coconut tree, so the best match would be the rightmost image. These problems are come under semantic gap.

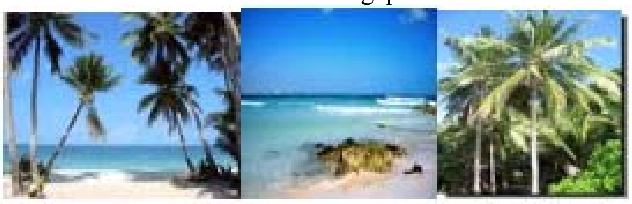

Fig. 2 Example of semantic gap

III. RELEVANCE FEEDBACK(RF)

A question that naturally emerges is, what can we do to deal with these problems? The answer is introducing the users to the process, having them interacting and telling what is really relevant for the images being retrieved and analyzed. Therefore, by gathering the user's indications, algorithms can be developed to change the placement of the query, or to change the similarity function employed in order to better comply with the user's expectations. The approach that asks to the user to set the relevance of the images to a given query and to reprocess it based on the user's feedback is called relevance feedback (RF) [1],and is been proven to be quite effective in bridging the semantic gap.

The conventional process of Relevance Feedback is as shown below :

1. from the retrieved images, the user labels a number of relevant samples as positive feedbacks, and a number of irrelevant samples as negative feedbacks;
2. The CBIR system then refines its retrieval procedure based on these labeled feedback samples to improve retrieval performance.

Recently, lots of Relevance Feedback methods have been introduced and we classify them into the following groups.

1. Subspace learning based methods [2][3][4] define a ( )-class problem and find a subspace within which to separate the one positive class from the unknown number of negative classes. Few of the methods come under this category are: biased discriminant analysis or BDA[7],the direct kernel biased discriminant analysis (DKBDA)[6], marginal biased analysis (MBA) [5]

2. Support vector machine (SVM) based methods [8][9] either estimate the density of positive instances or regard Relevance Feedback as a classification problem with the positive and negative samples as training sets. SVM activelearning selects the samples near the SVM boundary and queries the user for labels. After training, the points near the SVM boundary are regarded as the most informative images while the most-positive images are the farthest ones from the boundary on the positive side.

3. Random sampling-based methods [1]apply statistical sampling techniques to reduce particular problems in Relevance Feedback which occurs in previous two methods. For example, the asymmetric bagging random subspace scheme [10][11].

4. Feature selection-based methods [5] [12] adjust weights associated with various dimensions of the feature space to enhance the importance of those dimensions that help in retrieving the relevant images and to reduce the importance of those dimensions that hinder the retrieval performance. Alternatively, features can be selected by the boosting technique, e.g., AdaBoost,[13], in which a strong classifier can be obtained as a weighted sum of weak classifiers along different feature dimensions.

IV.IMPLEMENTATION DETAILS

Relevance Feedback (RF) is one of the most powerful techniques to bridge the semantic gap by letting the user label semantically relevant and non relevant images, which are positive and negative feedback samples respectively. One-class support vector machine (SVM) can calculate approximately the density of positive feedback samples. Concerning the positive and negative feedback samples as two different classes, Relevance Feedback can be considered as online binary classification problem. This is the reason for finding better classifier, which can classify the images in the database based on user feedback. Two-class Support Vector Machine was widely used to build the Relevance Feedback schemes due to its superior generalization ability. With the observation that all positive samples are alike and each negative sample is negative in its own way, Relevance Feedback was formulated as a biased subspace learning problem, where there are an unknown number of classes, but the user is concerned only about the positive one.

A.. Support Vector Machine (SVM)

Support vector machine (SVM) active learning can select ambiguous samples as the most informative ones for the user to label with the help of the optimal hyper plane of SVM, and thus alleviate the labeling efforts of conventional Relevance Feedback.

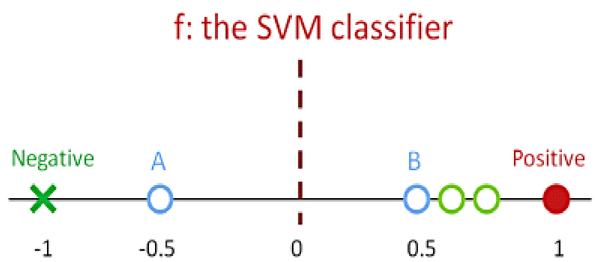

Fig. 3 Mechanism of SVM.

To explain the mechanism of SVMactive, a simple example of a toy is illustrated in the Fig.. 3. There are two labeled samples (i.e., the red solid dot • for the positive feedback sample while the green cross point × for the negative feedback sample) and several unlabeled ones (i.e., open circles ◦). The six samples distribute along a line and the coordinates on the horizontal axis indicate their positions. By using the SVM, the optimal hyperplane of the classifier f, which separates the two labeled feedback samples with a maximum margin, crosses position 0 as shown in the Fig.. 3 with the dashed line. According to the most ambiguous criterion, i.e., the samples closest to f have the maximum ambiguity, we can get that A and B have the maximum and identical ambiguity because they have the same distance, i.e., 0.5 for both, to the optimal hyper plane. Therefore, A and B should be identified by the user and used as the training data in Relevance Feedback. If we can choose only one sample for labeling, it is more reasonable to label B than A since more unlabeled samples are distributed around B and thus B is more effective than A to represent the distribution of unlabeled samples in the database. However, SVMactive can only select the ambiguous samples for the user to label although labeling representative ones may bring more useful information for achieving much better performance. Moreover, the optimal hyperplane of SVM is always unstable with smallsized training data [4], [5], i.e., this hyperplane is always sensitive when the size of the training data is small. Generally, in Relevance Feedback, the user would only label a small number of samples and cannot label each sample accurately all the time. Therefore, the optimal hyperplane of SVM cannot always be accurate with insufficient and inexactly labeled feedback samples.

B. Mathematical Model

User gives the query in the form of image Iq. The system retrieves Top K images from the image database. On retrieved images user will give feedback as positive and negative image samples. These image samples are then used for feature selection which will be further given to the classifier for classification. The proposed system S is defined as follows:

S = {I, Iq, F D, OI, RF, F S, F, ORF}

where, I = { I_1, I_2, ...IN }

I = set of images in a database.

N = number of images.

Iq = Query image.

FD = { FD_1, $F D_2$, ...$F D_N$ }

FD = set of vectors in the database

N = Number of images where FDi ={ FD_{i1}, FD_{i2}, ...FD_{id}} is a set of d features associated with each feature vector.

OI = { OI_1, OI_2, ...OI_k}

OI = set of retrieved images as output

ORF = set of positive and negative labelled samples given by user on retrieved images

FS = { FS_1, FS_2, ..FS_M}

FS = set of features selected from the feature database

F= { F_1, F_2, ...}

Where F is a set of functions.

Functionality of this system is to output top K images which are relevant to the query image given by the user.

C. Process Block Diagram

The block diagram for proposed system is shown in Fig. 4. Relevance Feedback approach consists of different stages

1. Retrieval: These are the retrieved images which are relevant to the query image provided by the user.

2. **Relevance Feedback:** Now user will ask to label the images as relevant or non relevant as positive and negative feedback samples

3. **Feature Selection:** The features which are most dominating are selected from the relevance between positive images.

4. **Binary Classifier:** This feedback data is given to the classifier as a training data for classifying the images in the database into two classes as positive and negative.

5. **Re-ranking:** After classification the images in the database are ranked again.

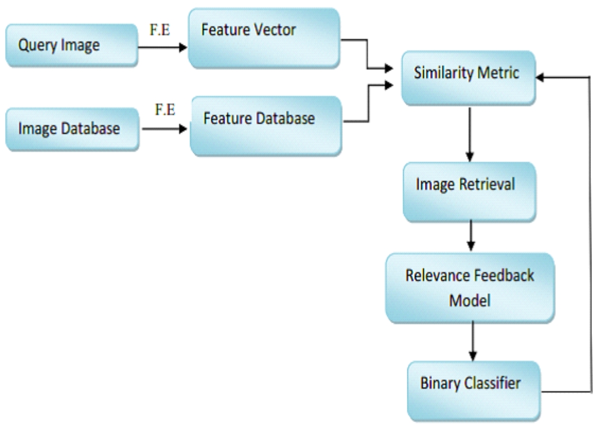

Fig. 4. System Architectural Diagram.

D. Outcomes

Outcomes of this system are:

1. When a query image is given to the system all images in database are ranked as per their relevance with query image and top K images are retrieved.

2. Worst, moderate and best case queries are selected to study experimentally the effect of Relvance Feedback on system performance.

3. Also for a given query, precision is calculated at different recall values considering entire database and is displayed.

V. Results And Discussion

The precision and recall will be computed to evaluate the performance of retrieval system.

Precision= The Number of relevant images retrieved/Total Number of relevant images.
Recall= Number of relevant images retrieved/Total Number of images retrieved.

A. Experimental Setup

In order to assess the performance of the proposed method, an image set containing 1000 images from the Corel database of natural jpg images is used. Initially all the images in the database are used once as queries. In each

Relevance Feedback round, at most 3 relevant images are to be selected. These images are used in combination with the examples provided in the previous Relevance Feedback rounds to select a number of important features(K) and, then, to train a new SVM classifier in the resulting lower-dimensional feature space. Based on this new classifier, the ranking of the database images is updated. For the initial ranking, when no feedback examples have been provided yet and, hence, neither feature selection nor classifier training can be employed, the Euclidean distance in the initial feature space is used.

VI. CONCLUSIONS

In this paper a new relevance feedback approach for CBIR system is presented . This approach uses binary classifiers to distinguish between the classes of relevant and irrelevant images, along with a SVM-based feature selection technique. As compared to existing systems, proposed system may give the better retrieval results. The precision and recall will be computed to evaluate the performance of retrieval system.

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