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PERFORMANCE IMPROVEMENT OF CONTENT BASED IMAGE RETRIEVAL SYSTEM USING RELEVANCE FEEDBACK

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Abstract: **Relevance Feedback (RF) approach refines the retrieval process and thereby improves the performance of CBIR system. Related works on CBIR are investigated and it was observed that existing Relevance Feedback techniques face the challenges of number of iterations and the execution time. To improve the retrieval efficiency of the existing system, the proposed RF approach makes use of binary classifier and a feature selection technique to reduce the dimensionality of the image feature space. The positive and negative examples provided by the user will be used to determine a small number of the most important features for the classification in every RF iteration. The trained classifier will be later used to provide an updated ranking of the database images represented in the space of the selected features.**

Keywords: *Content based image retrieval (CBIR), Relevance Feedback (RF), Iterations, Classification, Ranking.*

I INTRODUCTION

Relevance Feedback (RF) is an iterative process, which refines the retrievals by exploiting the user's feedback on previously retrieved results of CBIR system [1]. The RF techniques provide a way of bridging the gap between low level features used in CBIR system and high level semantic concepts. The RF techniques have been effective in accessing image database, and deal with a single query in a single retrieval session only.

The RF techniques can face two problems before applying to image retrieval [2]. First, it is hard to use supervised learning before the retrieval system is formed. The system has no information about which database images are relevant and which are not relevant to a set of known labels, since user's purpose is not known until user gives the feedback. Since, most users cannot label too many feedback samples, the information is limited. Second, image semantics is generally not described wholly by the low-level features, we need to conquer the dissimilarity between human subjects and machine subjects.

II LITERATURE SURVEY

The techniques used for Relevance Feedback include query vector modification (QVM) [4], [5], feature relevance estimation (FRE) [6], [7], [8], and classification-based (CB) methods [9], [10], [11], [12], [13].

In Query Vector Modification (QVM) method, the query vector of an image is modified after user's feedback. But QVM method has some weaknesses. First, every relevant image is not consistently relevant to the query along every feature dimension. Second, it is assumed that the location of the relevant images forms an intrinsic cluster which is valid for chosen distance function only.

In Feature Relevance Estimation (FRE) method for each low-level feature, it learns the weight and computes the dissimilarity. The weaknesses of FRE method includes, the relevant images may not be selected though they are neighbor of a query. Only the feature relevance is calculated so the identity of relevant images is not stored.

In Classification Based (CB) method, a classifier is trained from the former history of feedbacks for classifying the test data.

Support vector machines (SVM) are a core machine learning technology [14]. SVM hyper-planes separate the training data in a space by a maximal margin rule. The best hyper-plane is the one that maximizes the margins in the data space. However, the optimal hyper plane of SVM is usually unstable and inaccurate with small-sized training data.

To improve the performance of existing CBIR system, it is very important to find effective and efficient Relevance Feedback mechanisms. Related work on Relevance Feedback techniques is examined and it was observed that existing RF techniques face the challenges of number of iterations and execution time. If the labeled feedback is given to the binary classifier after selecting the dominating features among positive image samples, proficiency of existing CBIR system can be improved

III 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 estimate the density of positive feedback samples. Regarding the positive and negative feedback samples as two different classes, RF 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 SVM was widely used to construct the RF schemes due to its good generalization ability. With the observation that all positive samples are alike and each negative sample is negative in its own way, RF was formulated as a biased subspace learning problem, in which there are unknown numbers of classes, but the user is only concerned about the positive one. The conventional process of RF includes

1. From the retrieved images, the user labels a number of relevant samples as positive feedbacks, and a number of non relevant samples as negative feedbacks.
2. The CBIR system then improves its retrieval process based on these labeled feedback samples to improve retrieval performance.

The system will perform as a Relevance Feedback system for CBIR, which will use binary classifier. The input to the system is the retrieved images of the existing CBIR system. The user will label the images as positive and negative as a feedback to the system. These labeled images are then used as training data to train a classifier. Classifier will classify the images in the database into two classes as positive and negative. After classification has been done, the images will be reranked as per their relevance to the user. Worst, moderate and best case queries are selected to study experimentally the effect of RF on system performance in terms of precision and recall.

A. PROBLEM SOLVING APPROACH

Content based image retrieval (CBIR) system is an automated technique that takes an image as query , extracts low level features from the query image, matches it with the features of stored images from the database and returns a set of images similar to the query. If the user is not satisfied with the retrieved images, the user assesses images as relevant or irrelevant to the query and provides this assessment as feedback to the system. Relevance Feedback is an interactive process between the user and the retrieval system. This feedback is used to update the ranking criterion to retrieve a new set of images with feature selection based on minimum variance method to select most important and dominant features in each RF round.

B. EFFICIENCY ISSUES

There are different measurement criteria for efficiency calculation. The main goal is to improve the precision and recall. Efficiency is to be improved by incorporating user’s feedback on the retrieved results. If the number of training samples is large then the accuracy of classification is greater. But there is a limitation on number of retrieved images shown to the user. Hence this number can be limited at 10 percent and 20 percent recall. The important and dominant features are selected using minimum variance method to train a classifier which reduces the dimensionality of feature vector. Minimum variance method is simple to implement and makes the interaction fast. Dimensionality reduction of feature vector reduces the retrieval time required in each RF round. It is also expected that the user should be satisfied with less number of feedback rounds. Hence the rate with which the system is improving its performance per feedback round should be as high as possible.

C. MAJOR CONSTRAINTS

The general assumption is that every user need is different and time varying, the database cannot adopt a fixed clustering structure and the total numbers of classes are not available before-hand since these are assumed to be user dependent. If the number of training samples is small relative to the dimension of the feature space and the number of classes is large for most real world databases then SVM cannot give stable or meaningful results, unless more training samples can be provided by the user.

Finally, since the user is interacting with the machine in real time, the algorithm should be sufficiently fast and avoid heavy computation over the whole dataset if possible.

The architecture of the proposed system is shown in Fig. 1. Relevance Feedback approach consists of different stages

D. ARCHITECTURAL DESIGN

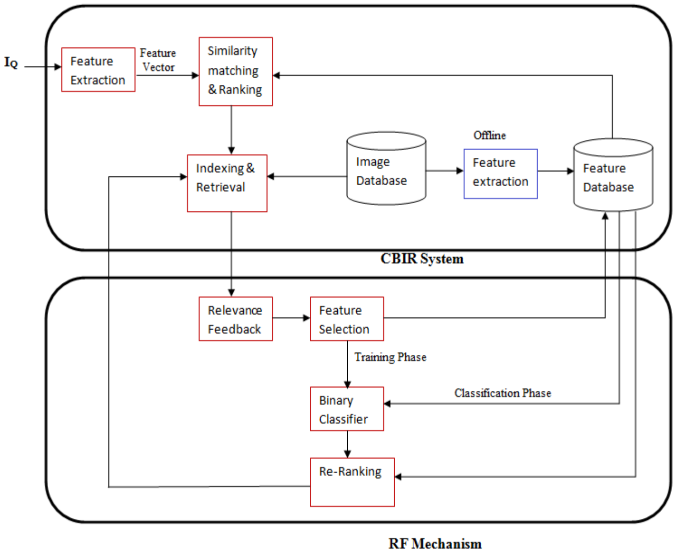


Figure 1. System Architecture

Feature Extraction: CBIR system extracts features as per predetermined scheme from each image present in image database and stores the feature vectors in feature database. It is offline process. Performance of retrieved process depends on the feature extraction scheme used by the CBIR system.

Similarity matching and Ranking: When user provides a query in the form of image, the system extracts features and forms a feature vector. It is then compared with the feature vectors stored in the feature database and using similarity metric the images are ranked as per their relevance with the query image.

Indexing and Retrieval: The system will retrieve the images from image database which are relevant to the query image provided by the user based on similarity matching and ranking.

Relevance Feedback: Images retrieved by the CBIR system will be provided to the user. In each RF round, user will respond to the system by marking the images as relevant or non relevant to the query submitted as per his/her subjective opinion. The marked images are treated as positive and negative feedback samples. User is allowed to carry out the RF rounds up to his/her satisfaction. At the end of every round, retrieval performance is improved and precision/recall table is modified.

Feature Selection: It is the process of selecting a subset of features FS = {FS1, FS2, …..FS_M}, more relevant to the query image. The features which are non-relevant or redundant with respect to query image are removed while preserving informative and important features. Feature selection techniques based on minimum variance method can be applied in each RF round. Initially mean is calculated of all features in feature vectors of positive feedback samples. From mean, deviation and variance are calculated. Features are sorted in ascending order of their variance and a dynamic threshold is set. The features below the threshold value are used to train SVM classifier.

Binary Classifier: The SVM classifier is used as binary classifier. The subset of features FS generated in feature selection is given to the classifier as input.

Reranking: After classification, images in the database which are in relevant class IR and far from the hyper plane are ranked again in descending order.

IV RESULTS AND DISCUSSION

Corel database of 1000 natural jpg images are used as test database. Database includes 10 categories; each category contains 100 images of similar type. Size of all images is either 256 X 384 or 384 X 256. Figure.2 shows sample images from Corel data set in 5 categories viz African, Beach, Building, Buses, and Dinosaurs.

Figure 2. Sample images from Corel Data Set

A.Performance Metrics

The precision and recall will be computed to evaluate the performance of retrieval system. For a query q, images in the database that are relevant to the query q is denoted as R(q), and the retrieval result of the query q is denoted as Q(q). The images which are relevant but are not retrieved from the database is denoted by N(q). The precision of the retrieval is defined as the fraction of the retrieved images that are indeed relevant for the query.

$$\text{Precision} = \frac{R(q)}{Q(q)}$$

The recall is the fraction of relevant images that is returned by the query.

$$\text{Recall} = \frac{R(q)}{R(q)+N(q)}$$

Usually, a tradeoff must be made between these two measures since improving one will sacrifice the other. In typical retrieval systems, recall tends to increase as the number of retrieved items increases; at the same time the precision is likely to decrease.

B.Experimental Setup

In order to assess the performance of the proposed system, an image set containing 1000 images from the Corel database of natural jpg images is used. These images are manually classified into 10 semantic categories, and this categorization will be the ground truth of the RF simulations.

Because the ground truth of the whole database is known, every image in the database will be used as a query. For each query, the precision for the retrievals at 10% and 20% level of recall will be obtained.

All the 1000 images from the database are used once as a query. Initial ranking is provided by the existing CBIR system. Experiment is performed on 2 different CBIR systems viz. CBIR system 1 and CBIR system 2.

CBIR system 1 uses SIFT (Scale Invariant Feature Transform) algorithm for feature extraction. SIFT is an algorithm for extracting stable feature description of objects called key points that are robust to changes in scale, orientation, shear, position, and illumination. A feature vector of 128 dimension is generated. In the bag of words model, the feature space is divided by applying the k-means clustering algorithm to the SIFT feature descriptors. Then each descriptor is assigned to one or more clusters with closest centers. Instead of storing a whole descriptor cluster number is stored. A bag of words is a sparse vector of occurrence counts of words (or clusters).

Similarity matching is the process which compares query image feature vector with already stored feature vectors in image database. It is based on similarity measure (Bhattacharya Distance) to calculate distance between the query image feature vector and feature database. The Bhattacharyya distance measures the similarity of two discrete or continuous probability distributions. Depending on similarity measure it generates a list of images for retrieval.

CBIR system 2 uses RGB color features and a color histogram. For each image the sum of R, G, and B color components and mean of R, G, and B color components are obtained as color features based on which a color histogram is formed.

Similarity matching is based on Euclidean Distance and it is calculated between the query image feature vector and each feature vector present in feature database. The feature vectors are sorted in ascending order of their distance from query image feature vector. Depending on similarity measure it generates a list of images for retrieval.

Experiment is divided into 2 categories

1. Selecting relevant images from top 10 images retrieved by the existing CBIR system.

2. Selecting relevant images from top 20 images retrieved by the existing CBIR system.

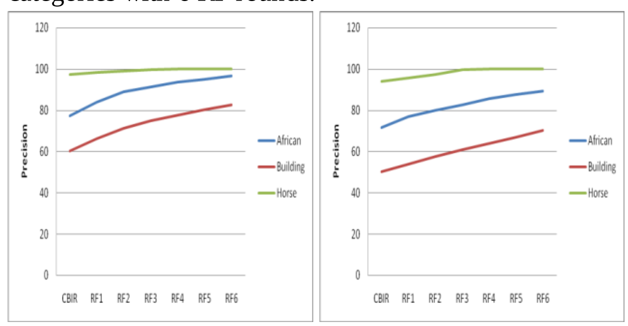
For each query image and for each category of experiment 6 RF rounds are performed and precision is observed at 10% and 20% recall that is observing the rank of 10th and 20th relevant image respectively in re-ranked image database.

For each RF round precision values are averaged over ten categories of images present in database. Results are tabulated separately for each category of experiment and for two different existing CBIR systems and represented using graphs.

C Experimental Results

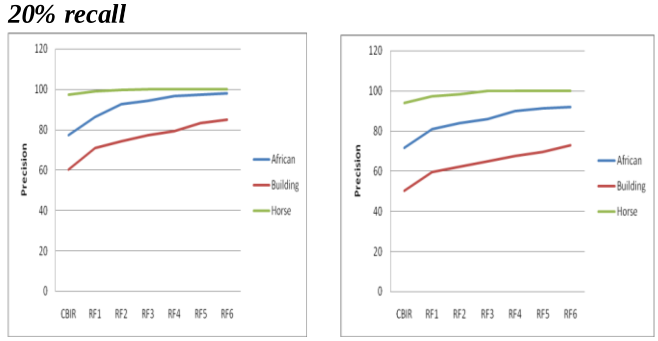
Fig. 3 shows the experimental results obtained at 10% and 20% recall by selecting feedback samples from top 10 images retrieved for CBIR system 1 for any three categories with 6 RF rounds.

Fig. 4 shows the experimental results obtained at 10% and 20% recall by selecting feedback samples from top 20 images retrieved for CBIR system 1 for any three categories with 6 RF rounds.



(a) (b)

Figure.3 Samples selected from top 10 images retrieved and average precision is calculated (a) at 10% recall and (b) at 20% recall

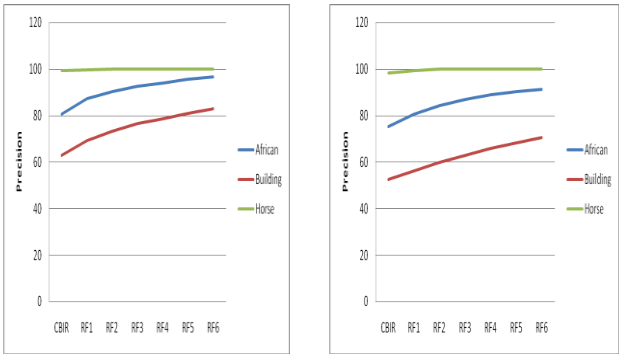


(a) (b)

Figure.4Samples selected from top 20 images retrieved and average precision is calculated (a) at 10% recall and (b) at 20% recall

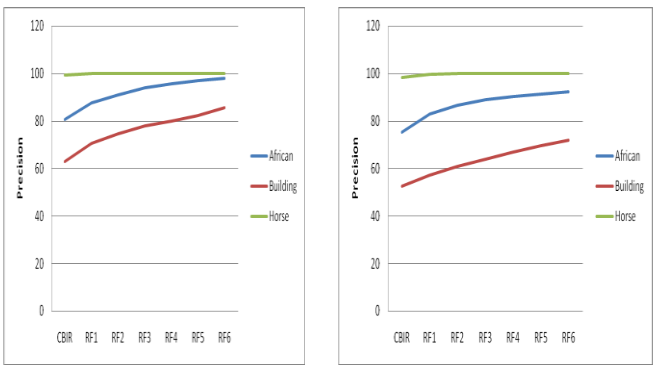
Fig. 5 shows the experimental results obtained at 10% and 20% recall by selecting feedback samples from top 10 images retrieved for CBIR system 2 for any three categories with 6 RF rounds.

Fig. 6 shows the experimental results obtained at 10% and 20% recall by selecting feedback samples from top 20 images retrieved for CBIR system 2 for any three categories with 6 RF rounds.



(a) (b)

Figure.5 Samples selected from top 10 images retrieved and average precision is calculated (a) at 10% recall and (b) at 20% recall



(a) (b)

Figure.6 Samples selected from top 20 images retrieved and average precision is calculated (a) at 10% recall and (b) at 20% recall

Table 1 shows the performance comparison of CBIR system in terms of average precision over all categories with and without feedback at 10% and 20% recall.

TABLE 1
PERFORMANCE COMPARISON OF CBIR SYSTEM

	CBIR System 1		CBIR System 2	
	10% Recall	20% Recall	10% Recall	20% Recall
Without Feedback	73.85	66.64	78.71	73.43
Feedback Samples Selected from top 10 retrieved images	89.10	81.99	92.65	87.64
Feedback Samples Selected from top 20 retrieved images	91.05	84.36	93.74	88.76

Table 2 shows the Performance comparison of CBIR system in terms of maximum improvement in average precision for any single category at 10% and 20% recall.

TABLE 2
PERFORMANCE COMPARISON OF CBIR SYSTEM

	CBIR System 1		CBIR System 2	
	10% Recall	20% Recall	10% Recall	20% Recall
Feedback Samples Selected from top 10 retrieved images	22.32	21.91	27.52	24.55
Feedback Samples Selected from top 20 retrieved images	25.24	25.43	28.84	25.65

V CONCLUSION

A relevance feedback approach is used to improve the performance of CBIR system. Feature selection based on minimum variance method is used to select dominant features among all positively marked images. SVM classifier is trained using positively marked feedback samples. The trained classifier is used to distinguish between relevant and irrelevant images present in image database. The experimental results demonstrate the effectiveness of the proposed RF mechanism with respect to the existing CBIR systems.

From the experimental results shown in graph it is observed that average precision for each category of images goes on improving in each RF round. The significant thing about average precision is that improvement is higher for the categories for which existing CBIR system was giving poor average precision. If more number of positive feedback samples made available in each RF round then for each category of images more improvement is expected. And the experimental results also show the same thing that is higher improvement is observed in selecting feedback samples from top 20 retrieved images compared to those selecting from top 10 retrieved images.

It is also observed that among all the experiments the maximum improvement (28.84) in average precision is observed under Mountain category at 10% recall when feedback samples selected are from top 20 retrieved images provided by CBIR system 2 that is improving from 63.42 to 92.26. Also from table 9.11, it is observed that maximum improvement is more for CBIR system 2. Table 9.10 provides the comparison of performance in terms of average precision at 10% and 20% recall for both categories of experiments conducted over all categories of images. The effectiveness of proposed RF mechanism is evident from this table.

VI FUTURE ENHANCEMENT

The proposed system clearly makes the improvement in performance of CBIR system. But still there is a scope to improve the performance at faster rate that is in minimum feedback rounds to achieve this; the classification can be based both on positive as well as negative feedback samples provided by the user. Also instead of using a simple feature selection method used in proposed system, a more sophisticated algorithm can be employed.

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