# Improving the Performance of Content Based Image Retrieval System using Relevance Feedback

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*Abstract*-**The performance of the CBIR system can be improved by reducing the semantic gap between visual features and human semantics. Relevance Feedback (RF) approach refines the retrieval process with users feedback on Content based image retrieval (CBIR) system results. A variety of Relevance Feedback (RF) methods have been widely used to reduce the semantic gap. 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 uses classification based method. The positive and negative examples provided by the user will be used for the classification. A binary classifier will be trained to distinguish between relevant and irrelevant images according to the preferences of the user. 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, binary Classifier**

## 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]. In Content based Image Retrieval (CBIR), user initializes a session by giving a query image as input. The system then compares the query image to each image in the database and returns k images that are the nearest neighbors to the query. If the user is not satisfied with the retrieved result, the user can stimulate Relevance Feedback (RF) process by identifying and labeling retrieved images as relevant and non relevant which can be used as positive and negative feedback samples. The process is repeated until the user is satisfied or the results cannot be further improved. 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. Currently, the Support Vector Machine (SVM) based Relevance Feedback methods are popular because they outperform other classifiers.

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.

This paper is organized as follows: Section I describes a brief introduction of image retrieval and motivation of the proposed system. Section II describes the related work in which we describes the motivational survey, efficiency and drawbacks of previous system. Section III describes the programmers design. Section IV describes the result parameters, experimental setup and result table. And finally in Section V, we conclude with the summary of this paper.

## 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].

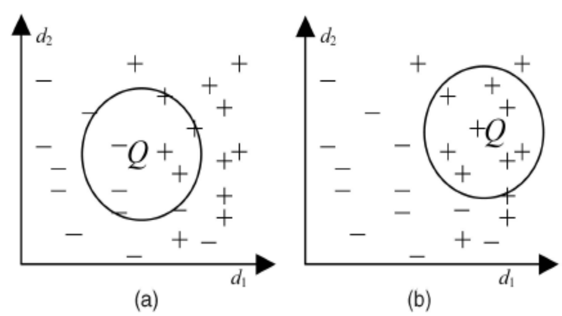


Fig. 1. QVM. (a) The original query. (b) The query is moved to a region that involves more relevant images. "+": relevant, "–": nonrelevant, and "Q": query.

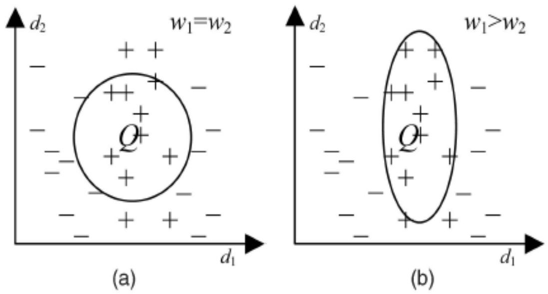


Fig. 2. FRE. The nearest neighborhood boundary forms (a) a circle with equal relevances and (b) an ellipse with different relevances. "+": relevant, "–": nonrelevant, and "Q": query.

In Query Vector Modification (QVM) method, the query vector of an image is modified after user's feedback using

$$Q = \alpha Q + \beta \sum_{D_j \in R} \frac{D_j}{|R|} - \gamma \sum_{D_j \in N} \frac{D_j}{|N|},$$

Where, Dj are images in the relevant set R or nonrelevant set N, and α, β, and γ are the weights. The query is moved toward relevant images and away from nonrelevant ones (Fig. 1).

The 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 (Fig. 2), for each low-level feature $d_i$, it learns the weight $w_i$ and computes the dissimilarity using

$$Dist(Q, D) = \sqrt{\sum_{i=1}^{t} w_i (q_i - d_i)^2}.$$

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]. SVMs are basically used for binary classification.

SVM hyper-planes separate the training in a data space by a maximal margin rule. The best hyper-plane is the one that maximizes the margins in the data space. The training instances that lie closest to the hyper-plane on each side of it are called support vectors, and a margin is defined as the minimum distance of support vectors from the hyper-plane. SVM selects ambiguous samples for the user to label with the help of the optimal hyper plane. 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 an unknown number 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 and the precision and recall will be computed.

### A. *RF using SVM*

Let, the binary classification problem $\{(xi, yi)\}^{N}_{i=1}$, where $x_i$ are the labeled patterns and $y_i \in \{-1, +1\}$ the corresponding labels. SVM classifier will be trained using training data [3]. Then SVM classifier maps these patterns to a kernel space, using a transformation $x \rightarrow \ell(x)$. This new space can be nonlinear and of much higher dimension than the initial one. A linear decision boundary is computed after mapping in the kernel space. The problem of classification is addressed by maximizing the margin, which is defined as the smallest distance in the space, between the decision boundary and any of the training patterns.

After training of the classifier, the value of the decision function for a new pattern x is computed by:

$$y(x) = \sum_{i=1}^{N} a_i y_i k(x_i, x) + b \tag{1}$$

Where, b is a bias parameter. The value $|y(x)|$ is proportional to the distance of the input pattern x from the decision boundary. Thus, the value y(x) can be regarded as a measure of confidence about the class of x, with large positive values (small negative values) strongly indicating that x belongs to the class denoted by +1 (−1). Similarly on the other side, values of y(x) around zero provide slight information about the class of x.

It is clear that after classification using SVM classifier based on the feedback examples it is used to distinguish between the classes of relevant and irrelevant images. Each image in the database will be given to the trained classifier and the value of the decision function will be used for ranking criterion. The higher the value of the decision function for an image, the more relevant this image is considered by the system.

### B. *Process Block Diagram*

The block diagram for proposed system is shown in Fig. 3. Relevance Feedback approach consists of different stages

Image Retrieval: A CBIR system will retrieve the images from database which are relevant to the query image provided by the user. Performance of retrieval process depends on the features which are extracted by the CBIR system.

Relevance Feedback: User will mark the images as relevant or non relevant to the query image provided. The marked images are treated as positive Ip and negative In feedback samples.

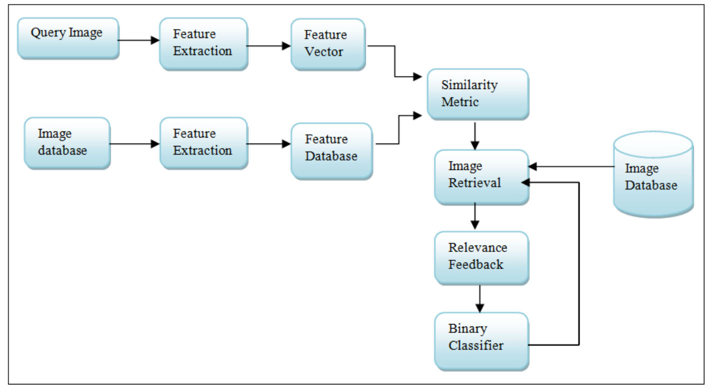


Fig. 3. System Architectural Diagram

Binary Classifier: The features of positive marked images are given to the classifier as a training data for classifying the images in the database into two classes as relevant IR and non relevant INR. The feature vectors correspond to the feedback examples provided by the user and each image is labeled as +1 or -1 corresponding to relevant or non relevant, respectively. The initial query is considered to be one of the relevant images and is labeled as +1. Each image in the database will be presented to the trained classifier.

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 & DISCUSSION

### A. *Performance Metrics*

The precision and recall values are used to evaluate the performance of retrieval system. The number of images in the database that are relevant to the given query q is denoted as R(q), and the number of images that are retrieved for the query q is denoted as Q(q). The images which are relevant but 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 retrieved for 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; while 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. Size of all images is either 256 X 384 or 384 X 256.

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 each level of recall (10%, 20%,...,100%) will be obtained. Worst, moderate and best case queries are selected to study experimentally the effect of RF on system performance.

### *C. Result Table*

Initially all the 1000 database images are used once as queries. For each query image we used 6 RF rounds. In each RF round, at least 3 relevant images are to be selected randomly. Based on this new classification, the ranking of the database images is updated. Initial ranking is provided by the original CBIR system without relevance feedback.

Precision is calculated for 10% and 20% recall for all the 10 categories of Corel dataset.

Table 1: Average precision for 10% recall

| **Category** | **CBIR** | **RF 1** | **RF 2** | **RF 3** | **RF 4** | **RF 5** | **RF 6** |
|---|---|---|---|---|---|---|---|
| African | 82.5 | 89.51 | 93.34 | 95.28 | 96.91 | 97.54 | 97.95 |
| Beach | 59.89 | 66.99 | 73.59 | 78.59 | 83.06 | 86.55 | 89.65 |
| Building | 78.09 | 85.14 | 89.4 | 92.51 | 94.17 | 95.5 | 96.72 |
| Bus | 79.19 | 85.67 | 89.04 | 91.74 | 94.06 | 95.82 | 97.39 |
| Dinosaur | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Elephant | 82.6 | 88.78 | 92.67 | 95.12 | 96.88 | 98 | 98.72 |
| Rose | 92.85 | 95.47 | 97.27 | 98.12 | 98.5 | 98.77 | 99.05 |
| Horse | 99.39 | 99.76 | 99.9 | 100 | 100 | 100 | 100 |
| Mountain | 63.41 | 69.94 | 75.76 | 80.24 | 83.57 | 87.22 | 90.83 |
| Dish | 80.89 | 85.65 | 88.53 | 90.88 | 92.33 | 93.52 | 94.24 |

Table 2: Average precision for 20% recall

| **Category** | **CBIR** | **RF 1** | **RF 2** | **RF 3** | **RF 4** | **RF 5** | **RF 6** |
|---|---|---|---|---|---|---|---|
| African | 78.21 | 84.68 | 88.93 | 91.5 | 93.21 | 94.96 | 95.47 |
| Beach | 52.64 | 57.35 | 62.16 | 66.93 | 71.25 | 75.52 | 79.26 |
| Building | 70.7 | 76.42 | 81.67 | 85.59 | 88.72 | 91.45 | 93.1 |
| Bus | 74.05 | 78.57 | 82.43 | 85.66 | 88.94 | 91.95 | 93.67 |
| Dinosaur | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Elephant | 74.69 | 79.29 | 83.6 | 87.78 | 91.01 | 93.51 | 95.18 |
| Rose | 84.38 | 87.36 | 89.48 | 91.42 | 93.17 | 94.34 | 95.12 |
| Horse | 98.39 | 99.42 | 99.86 | 99.95 | 100 | 100 | 100 |
| Mountain | 60.38 | 65.39 | 70.25 | 74.48 | 78.39 | 81.78 | 85.03 |
| Dish | 76.25 | 81.07 | 83.8 | 86.48 | 88.53 | 90.15 | 91.4 |

## CONCLUSION

In this paper a relevance feedback approach is used for CBIR system. SVM classifier is used to distinguish between relevant and irrelevant images according to the feedback examples. The experimental results demonstrate the superiority of the proposed method compared with the existing CBIR systems. Average precision is enhanced by a minimum of 0.61 to a maximum of 29.76 for 10% recall and average precision is enhanced by a minimum of 1.61 to a maximum of 26.62 for 20% recall after 6 rounds. The effectiveness is evident from the improvement of precision value particularly for beach and mountain category of images. Thus, the performance of CBIR system is improved in terms of precision and recall. In the future, we aim to generalize this approach.

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