Dynamic Feature Weights with Relevance Feedback in Content-Based Image Retrieval

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Abstract— **In this paper, we present a novel relevance feedback method for Content-Based Image Retrieval systems based on dynamic feature weights. The proposed method utilizes intra-cluster and inter-cluster information for representing the descriptive and discriminative properties of the features according to the labeled images by the user. Afterwards, feature weights are updated dynamically according to the user's preferences for improving retrieval results. The proposed method has been thoroughly evaluated and selected results are illustrated in the paper. It is shown that, satisfactory improvements can be achieved with small number of iterations and labeled samples. Furthermore, it is a low-complex and flexible method that can be used on various databases and Content-Based Image Retrieval applications.**

Relevance feedback, content-based image retrieval, low-level features, feature weights.

I. Introduction

Content is usually represented with low-level and high-level features in Content-Based Image Retrieval (CBIR) systems. Several low-level descriptors have been proposed recently in the domain of image indexing, retrieval and classification. High level features are also known as logical, semantic features. High level features involve various degrees of semantic existing in images, video and audio. They can be classified as objective or subjective features.

Subjective features concern the abstract attributes. They describe the meaning and purpose of objects or scenes. The use of low-level features does not yield satisfactory retrieval results in many cases; especially, when high-level concepts in the user's mind are not easily expressible in terms of low-level features. This challenge is called "semantic gap" between low-level feature vector representation and semantic concept of image content, which has recently been a popular research area involving studies on relevance feedback, annotation of images, and classification. Relevance feedback is found to be one of the most powerful methods for improving image retrieval performance [14]. Relevance feedback methods predict and learn user's preference to improve retrieval results. It interacts with user during the query in order to get user's subjective perception for improving the query results. The iterated relevance feedback results may guarantee improved retrieval results of image content data.

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Relevance feedback is a user-centered approach based on the following ideas:

- Relevant images should be more strongly similar to each other than non-relevant images
- Users are the best judges of relevance.

The studies presented in this paper are based on the motivation described above. In this paper, a dynamic feature weight update mechanism with relevance feedback is presented. The rest of the paper is organized as follows: Section-2 introduces the relevance feedback methods in the literature, and Section-3 briefly discusses the proposed method and algorithms. Section-4 presents the experimental results. Finally, Section-5 concludes the paper along with some future remarks.

II. Relevance Feedback in CBIR

Semantic refers to the meaning of the image content, which is a high-level concept compared to low-level visual features. Current CBIR systems often use low-level features such as color, texture, and shape. In this respect, one of the most important challenges in CBIR systems is to bridge the semantic gap between low-level features and high-level semantics. Visual features such as color, in general do not necessarily match perceptional semantics of images. To improve the semantic retrieval results, human perception subjectivity may be incorporated into the retrieval process by providing an opportunity for user to evaluate the results. This technique is called Relevance feedback, and it has become common research study in CBIR area [2], [4], and [5]. Relevance feedback is an iterative process, which improves the retrieval accuracy of content-based image retrieval by modifying the query based on the user's feedback for the retrieval results. Long and Leow in [7] proposed an approach of improving retrieval performance by increasing the perceptual consistency of computational features and similarity measurements. They proposed a method for measuring the perceptual distances and constructing perceptual space based on relevance feedback. Several frameworks use additional metadata with low-level features in order to bridge the semantic gap [1]. Zhang et. al. in [12] investigated the role of user term feedback in interactive text-based image retrieval. Term feedback refers to the

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feedback from a user on specific terms regarding their relevance to a target image.

Several relevance feedback approaches have been proposed in the literature [14]. Previous works on relevance feedback have been formulated in terms of a classification problem [13]. These techniques require a careful design, as the number of training samples is usually small, while the number of features used to represent image content can be large.

Two learning techniques are widely used in relevance feedback systems: Support Vector Machines (SVM) and Discriminant Analysis (DA). Support Vector Machines are most common approaches in the Pattern Recognition field, and the previously presented results are satisfactory compared to other classification techniques. There are two main disadvantages of the previous methods:

- It is a challenging task to choose an appropriate SVM kernel and associated parameters. Different values of the parameters and different choices of the kernel may reveal different performances. In general, the SVM results are presented without providing details on the effort spent for determining the most appropriate model.
- The computational complexity is high when an artificial network is involved in the relevance feedback process. The efficiency of a CBIR system becomes quite critical when usability of an application is evaluated. Additional to satisfactory retrieval results, the system should provide the results in a reasonable time to the end-user.

The proposed technique in this paper, as illustrated in Figure 1, is an instance-based method that formulates a new iteration of query and modifies the feature weights. The method takes into account the relevance of each feature to the user query in order to update the weights dynamically. It updates the feature weights through user iterations, instead of fixing them based on the samples. Therefore, the proposed method is straightforward, and efficient for CBIR applications. The main advantages of the proposed method and distinctions from the previous methods can be listed as follows.

- The proposed method does not need training data, due to its instance-based characteristics unlike classification-based approaches.
- The method works well with small number of labeled samples.
- The computational complexity of the method is lower compared to the artificial learning networks. Hence, it may be employed in time-critical systems efficiently.
- The method works efficiently and successfully with small number of iterations.

The proposed technique and technical details are presented in the following section.

III. PROPOSED METHOD

In the proposed method, relevance feedback system learns the user's preferences in order to update weights of the low-level features individually for improving the retrieval results. The relevance of the feature to the user query should be determined for improving the retrieval results according to the user's preferences. Therefore, the weights of the features are calculated based on the positive and negative labeled images by the user. It is assumed that positive examples have common pattern, thus weights for those features should be increased. If negative examples have common pattern with the queried image, than that distance does not have reliable discriminative properties and corresponding weights should be decreased. The weights of the features are calculated as follows:

$$\omega_f^* = 1 - \frac{(\alpha_f^- + \alpha_f^+)}{2} \tag{1}$$

where α^+ and α^- represent the pattern properties among positive and negative labeled images accordingly. The pattern properties should be small for the optimal cases and thus weight will be increased for that particular *f* feature.

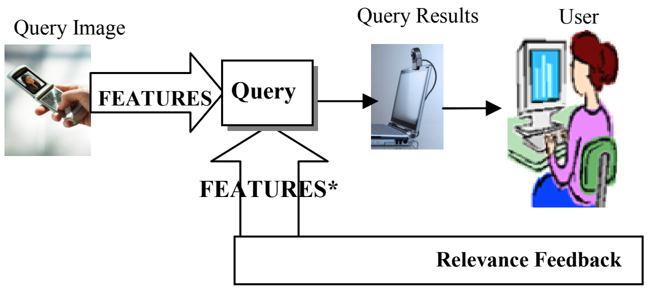


Figure 1: Proposed System Overview

In Eq.(1) α^+ and α^- are the relationship information factors describing the correlation between positive and negative labeled images. Djordevic and Izquierdo in [2], used variance in order to describe discrimination power of the feature. However, it should be considered that positive examples are in one class and negative examples may come from uncertain number of classes. Therefore, they should be handled separately. Positive examples may be evaluated with intra-class information, since they are supposed to be close in feature space. On the other hand negative examples may be handled with inter-class relation properties, and negative samples are expected to be distant in feature space. In a sample case, the intra-class α^+ value will be small for those positive labeled images that have common pattern, and thus this fact leads to increased weights of the feature. If the negative examples will be separate enough, than α^- value will be small and will cause again increase in the calculation of the weight.

In this paper, we use α^+ measure as intra-cluster information, Intra-Cluster Relation (ICR), which represents the intra-cluster scatter information using the principal component information of the cluster [3]. It is also related to the closeness of cluster elements similar to compactness. Intra-cluster scatter information is a widely used criterion in cluster analysis. The main objective of the intra-cluster analysis is to better understand the existing pattern in a given data space. ICR can be obtained by the following equation for a given set of feature vectors corresponding to positive labeled images:

$$\alpha^+ = ICR = \frac{\Delta}{\frac{2}{N(N-1)} \sum_{i=0}^{N-2} \sum_{j=i+1}^{N-1} d(x_i, x_j)} \tag{2}$$

where d is the Euclidean distance between positive labeled cluster members and N is the number of items. The calculation of sum of distances Δ and further details can be found in [3].

Inter-cluster information is widely utilized in cluster analysis for classifying data by using multiple features. The attributes of affinity between clusters (inter-cluster) represent the discrimination characteristics of a feature for a given data set. The data space is clustered with each feature individually, and the sums of correlations or distances are compared for evaluating the features. The criterion measuring class separability represents how the distances among the means of classes are maximized. Usually, this method is not used alone in feature selection approaches. The results become more reliable for discrimination if it is supplemented with intra-cluster information.

We use Pearson Product Moment Correlation (PPMC) for defining the correlation between negatively labeled images. PPMC is the most commonly used measure of correlation in machine learning. It is calculated by summing up the products of the score deviations from the mean. The PPMC value ranges from −1 to 1. A value of 1 shows that a linear equation describes the relationship completely, with all data points lying on the same line with direct proportion. A score of −1 shows that all data points lie on a single line with inverse proportion. A value of zero shows that there is no linear relationship between the variables. Thus, we use the absolute value of the PPMC in this paper.

We will use the following expression for the α^- measure;

$$\alpha^- = |\delta(x,y)| = \left| \frac{\sum_{i=1}^{N_x}(f_{xi}-\mu_x)(f_{yi}-\mu_y)}{N_x N_y \sigma_x \sigma_y} \right| \quad (3)$$

where f_{xi} and f_{yi} represents the i^th item in the cluster x and y, μ_x and μ_y , σ_x and σ_y are the means and the standard deviations, N_x and N_y are the cardinality of clusters x and y, respectively. Clusters x and y are assumed to have equal number of elements in order to be compared by PPMC. Further information on PPMC can be found in [3].

IV. Experimental Results

In the experiments, we used Corel real-world image databases for evaluating the retrieval results of the proposed method. Corel image data sets are well-categorized and widely used in the CBIR literature. For evaluating the results a Corel database with 5000 images are used. These images are pre-assigned by a group of human observers to 50 semantic classes each containing 100 images. The sample classes are: Africa, Beach, Buildings, Buses, Dinosaurs, Flowers, Elephants, Horses, Food, and Mountains. In the experiments, the following low-level color, shape, and texture features are used: YUV and HSV color histograms with 128-bins, Gray Level Co-Occurrence Matrix texture feature with parameter value 12, Canny Edge Histogram, and Dominant Color with 3 colors. 50 queries are performed on the database by selecting five images randomly from each class. Average precision values are calculated based on the retrieval results from these queries.

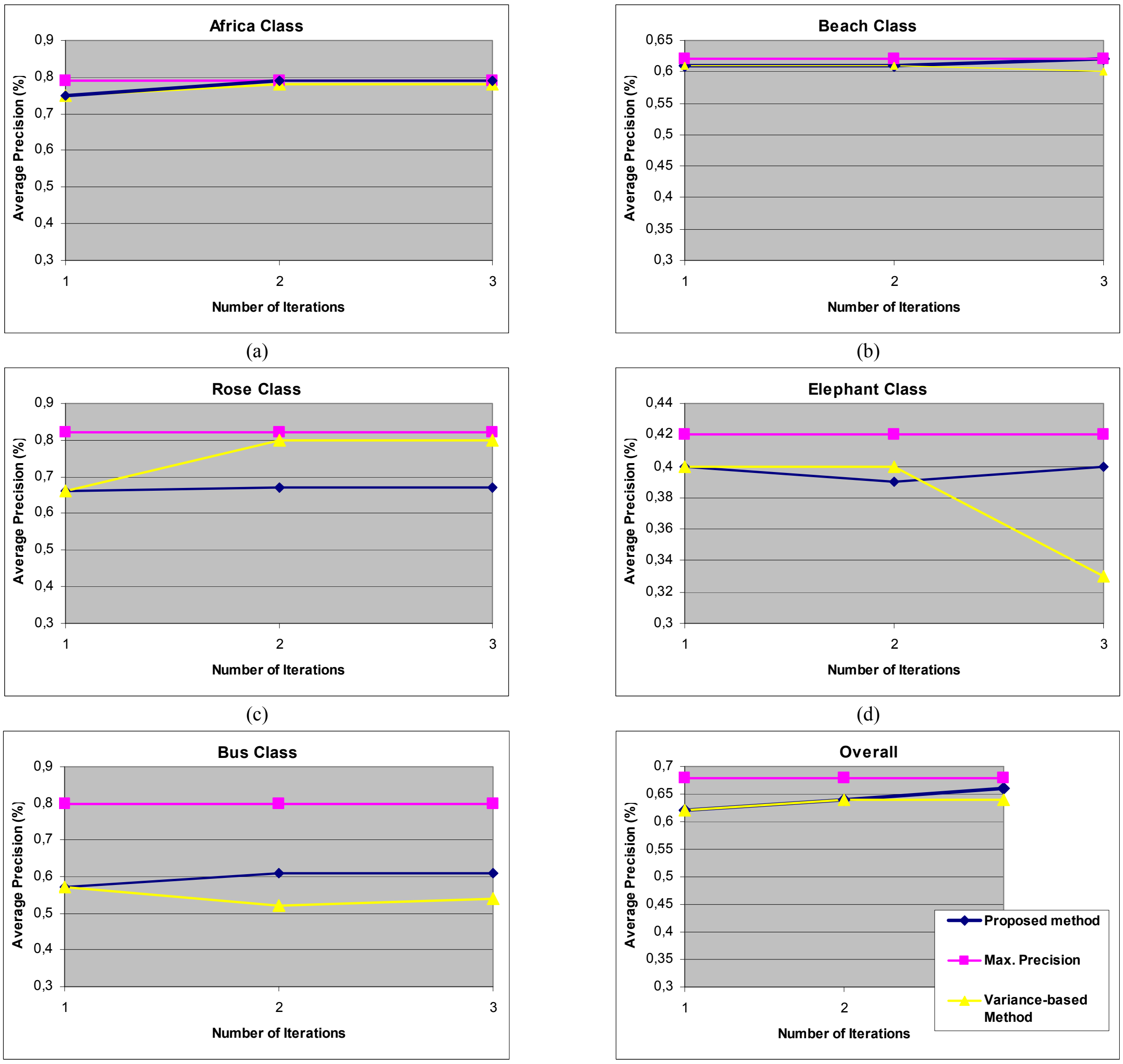
Figure 2 illustrates the experimental results with average precision values for five different classes and for overall image database. The straight lines in the graphs show the highest average precision score, which can be achieved with the existing low-level features in the database. As can be seen from the figures, the proposed method improves the retrieval results within one or two iterations. In other words, a small number of labeled samples are enough to improve the results. The method achieves the best average precision score in the database with utilized features for two classes with only one iteration. For the overall database, the method improves the retrieval results with one relevance feedback iteration, where only 10 labeled images are involved in the learning mechanism. The average numbers of positive and negative labeled images during the experiments are 15 (standard deviation is 5) and 6 (standard deviation is 4) respectively. These results verify our claim that, the proposed method achieves satisfactory performance with small number of iterations and feedbacks.

The proposed method is compared with variance-based feature weighting method presented in [2], and the results are illustrated in Figure 2. The weights are calculated based on variances of the distances of the positive and negative labeled images in feature space. It can be observed that, the proposed method has overall higher average precision values. This is due to the fact that, the distance variances of small number of labeled samples do not generalize the whole image database efficiently. For most categories there is a high variance in low-level features over different images.

V. Conclusions

A novel approach on dynamic feature weighting with relevance feedback in CBIR context is introduced in this paper. Two feature pattern properties based on intra-cluster and inter-cluster relations are utilized for the selection and combination of features. Intra-cluster information indicates the descriptive power of the feature and hence it is utilized to measure the positive labeled image cluster. On the other hand, inter-cluster information depicts the descriptive properties of the feature. Ideally, negative labeled images should be discrete in feature space. In this respect, these two metrics are utilized for dynamic feature weight calculation.

Two proposed criteria are compared with another feature weighting method through dedicated experiments, which show that the proposed methods improve retrieval performance. The proposed feature selection system is implemented as a black-box approach that gives flexibility for using it in different platforms. It may be applied on several types of databases and sets of features. Assessment studies on the criteria will be carried out using different databases on different platforms in the future. In addition, this work may be extended to multimodal features for multimedia databases.



(a) (b) (c) (d) (e) (f)

Figure 2 (a)-(f): Average Retrieval Precision of Selected Classes on Corel Image Database

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