Efficient Relevance Feedback for CBIR System

Priti P. Vaidya
Assistant Professor, Department of Computer Engineering
KKWIEER, Nashik, India

***Abstract*— The performance of the CBIR system can be improved by reducing the semantic gap between visual features and human semantics. Relevance Feedback (RF) approaches refines the retrieval process as per users' feedback. A variety of Relevance Feedback (RF) methods have been widely used to reduce the semantic gap. Related works on CBIR are also 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. In each RF iteration, 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. After the feature selection has been performed, a binary classifier will be trained to distinguish between relevant and irrelevant images according to the preferences of the user for the given query. The trained classifier will be used later 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); Feature selection; 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 with all images in the database and returns top 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 reiterated till the user's satisfaction or the results cannot be improved further. The Relevance Feedback 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 Relevance Feedback 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: In Section I, a brief introduction of image retrieval and motivation of the proposed system. Section II describes the related work in which we describe the motivational survey, efficiency and drawbacks of previous system. Section III describes the programmers design with Mathematical model. Section IV describes the result parameters. 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].

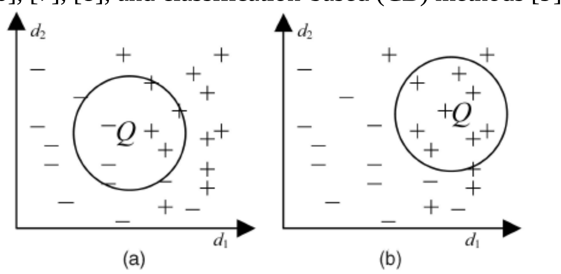

Fig. 1. QVM. (a) The original query. (b) The query is moved to a region that involves more relevant images. "+": relevant, "–": nonrelevant, and "Q": query.

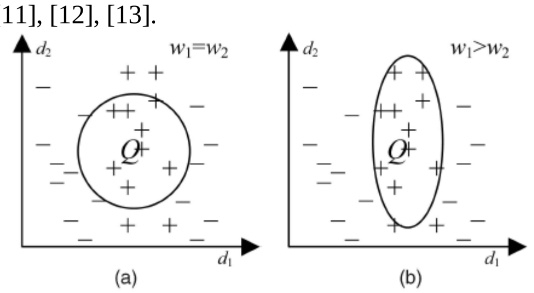

Fig. 2. FRE. The nearest neighborhood boundary forms (a) a circle with equal relevances and (b) an ellipse with different relevances. "+": relevant, "–": nonrelevant, and "Q": query.

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 di, it learns the weight wi 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]. SVM classifiers are fundamentally used for binary classification.

SVM hyper-planes separate the training in a data space by a maximal margin rule. The finest 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 least 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 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 RF 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, 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. The user labels a number of relevant image samples as positive, and a number of non relevant samples as negative feedbacks from the top k retrieved images.

2. The CBIR system then refines 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)}Ni=1, where xi are the labeled patterns and yi ϵ {−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 →ℓ(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 the training of the classifier, the value of the decision function for a new pattern x is computed by:

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

|y(x)| is the value proportional to the distance of the input pattern x from the decision boundary. Thus, y(x) can be regarded as a value of measure of confidence about the class of x, with large positive values (small negative values) strongly representing 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. b is a bias parameter.

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. If the value of the decision function is higher for an image then the image is considered more relevant by the system.

B. Feature Selection

Feature selection will be used to reduce the dimensionality of the patterns. Before training the classifier, the features which are not relevant and redundant are removed for distinguishing between the training set categories, while keeping informative and important features. As far as the problem of re-ranking the database images can be considered as a binary classification problem, feature selection techniques can be applied in each RF round.

In this work, we propose an RF scheme for CBIR using SVMs for the RF task along with the feature selection methodology introduced in [15].

The feature selection methodology called SVM Recursive Feature Elimination (SVM-RFE) is based on a recursive elimination of the less important features, based on the results of classification of the training patterns using SVM classifiers. This results in selecting those features which are the most important for the subsequent training of the SVM classifier used for RF.

Specifically, the SVM-RFE methodology is based on linear-kernel SVMs. Considering a linear SVM kernel:

$$k(x_i, x_j) = x_i^{\mathrm{T}} x_j$$

Equation (1), for the decision function will be:

$$y(x) = w^{\mathrm{T}} x + b \qquad (2)$$

And,

$$w = \sum_{i=1}^{N} a_i y_i x_i \qquad (3)$$

Where, the vector w is of the dimensionality similar to the training patterns xi. This form of decision function entails that the higher the value |wk| or w k2 for the k-th coordinate of the vector w, the larger is the influence of this coordinate on the value of the decision function for an unknown pattern x. This view provides a criterion to be used to rank the image features according to their importance for the classification task.

S_f is a set of all available features. As SVM-RFE is a recursive method, it updates a feature set Sf in each iteration, by eliminating the less important feature of the set. To determine the less important feature, it trains an SVM classifier with a linear kernel, using the training patterns restricted on the features currently included in Sf . After training, the feature with the smaller value wk2 is considered the less important one and is eliminated from Sf. This procedure is repeated until a predefined number of features remain in Sf.

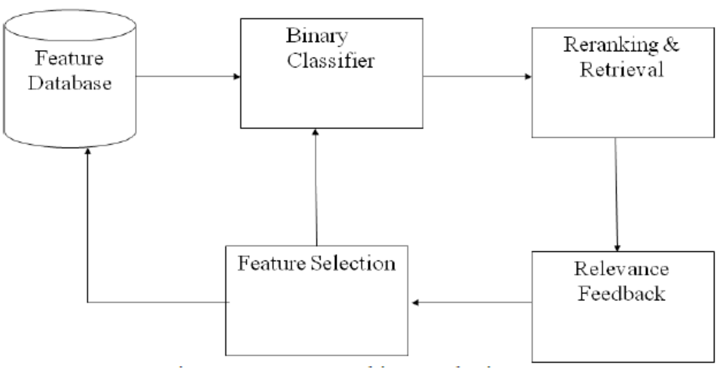

Fig. 3. System Architectural Diagram

C. Process Block Diagram

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

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

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

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

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

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

IV Results & Discussion

The precision and recall will be computed to evaluate the performance of retrieval system. For a query q, the images in the database that are relevant to the query image q is denoted as R(q), and the result of retrieval 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; while at the same time the precision is likely to decrease.

D. 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. 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 and vice versa.

The ground truth of the whole database is known so that every image in the database will be used as a query. For each query, the precision will be obtained at each level of recall (10%, 20%,...,100%) for the retrievals. Worst, moderate and best case queries are selected to study experimentally the effect of RF on system performance.

Initially all the images in the database are used once as queries. In each RF round, at most 3 relevant images are to be selected. These images are used in combination with the examples provided in the previous RF rounds to select a number, K, of important features 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.

V Conclusion

A new relevance feedback approach for CBIR is presented in this paper. This approach uses SVM classifiers to distinguish between the classes of relevant and irrelevant images, along with an SVM-based feature selection technique to reduce the feature space dimensionality according to the feedback examples. Furthermore, with a very large reduction of the features, a performance equivalent or even better compared to that obtained for the full feature set can be achieved. As compared to existing systems, proposed system may give the better retrieval results. And it will improve the performance of CBIR systems in terms of precision and recall.

VI Acknowledgment

I would like to express my sentiments of gratitude to all who rendered their valuable help. I am thankful to Prof. N. M. Shahane, for his guidance and encouragement in this work. His expert suggestions and scholarly feedback had greatly enhanced the effectiveness of this work. I am also thankful to Prof. S. M. Kamalapur for the interest shown in this work by timely suggestions and helpful guidance.

References

[1] Lining Zhang, Lipo Wang, Weisi Lin, Shuicheng Yan, “Geometric Optimum Experimental Design for Collaborative Image Retrieval”, IEEE Transactions on Circuits and Systems for Video technology, Vol. 24, No. 2, February2014

[2] Peng-Yeng Yin, Bir Bhanu, Kuang-Cheng Chang, and Anlei Dong,”Long Term Cross-Session Relevance Feedback using Virtual Features”, IEEE Transactions on Knowledge and Data Engineering , Vol. 20, No. 3, March 2008

[3] Apostolos Marakakis, Nikolaos Galatsanos, Aristidis Likas,” Relevance Feedback for Content-Based Image Retrieval Using Support Vector Machines and Feature Selection”, C. Alippi et al. (Eds.): ICANN 2009, Part I, LNCS 5768, pp. 942–951, 2009. Springer-Verlag Berlin Heidelberg 2009

[4] J.J. Rocchio, Jr., “Relevance Feedback in Information Retrieval,” The SMART System, G. Salton, ed., pp. 313-323, Prentice Hall, 1971.

[5] G. Ciocca and R. Schettini, “A Relevance Feedback Mechanism for Content-Based Image Retrieval,” Information Processing and Management,vol.35,no.6,pp.605-632,1999.

[6] Y. Rui et al., "Relevance Feedback: A Power Tool for Interactive Content-Based Image Retrieval," IEEE Trans. Circuits and Systems for Video Technology, vol. 8, no. 5, pp. 644-655, 1998.

[7] J. Peng, B. Bhanu, and S. Qing, "Probabilistic Feature Relevance Learning for Content-Based Image Retrieval," Computer Vision and Image Understanding, vol. 75, nos. 1-2, pp. 150-164, 1999.

[8] B. Bhanu, J. Peng, and S. Qing, "Learning Feature Relevance and Similarity Metrics in Image Databases," Proc. IEEE Workshop Content-Based Access of Image and Video Libraries (CBAIVL '98),pp. 14-18, 1998.

[9] C. Meilhac and C. Nastar, "Relevance Feedback and Category Search in Image Database," Proc. Int'l Conf. Multimedia Computing and Systems (ICMCS '99), pp. 512-517, 1999.

[10] I. Cox et al., "The Bayesian Image Retrieval System, PicHunter: Theory, Implementation, and Psychophysical Experiments," IEEE Trans. Image Processing, vol. 9, no. 1, pp. 20-37, 2000.

[11] S. Tong and E.Y. Chang, "Support Vector Machine Active Learning for Image Retrieval," Proc. ACM Int'l Conf. Multimedia, pp. 107-118, 2001.

[12] K. Tieu and P. Viola, "Boosting Image Retrieval," Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR '00), pp. 228-235, 2000.

[13] N. Vasconcelos and A. Lippman, "Learning from User Feedback in Image Retrieval Systems," Proc. Neural Information Processing System, 1999.

[14] M. L. Kherfi and D. Ziou, "Relevance feedback for CBIR: A new approach based on probabilistic feature weighting with positive and negative examples," IEEE Trans. Image Process., vol. 15, no.4, pp. 1017–1030, Apr. 2006.

[15] Guyon, I., Weston, J., Barnhill, S., Vapnik, V.: Gene Selection for Cancer Classification Using Support Vector Machines. Machine Learning 46, 389–422 (2002)

[16] L. Wang, K. Chan, and Z. Zhang, "Bootstrapping SVM active learning by incorporating unlabelled images for image retrieval," in Proc. IEEE Conf. Comput. Vision Pattern Recognit., 2003, pp. 629–634.

[17] Lei Zhang; Fuzong Lin; Bo Zhang; "Support Vector Machine Learning For Image Retrieval," in Image Processing, 2001. Proceedings. 2001 International Conference, pp 721 - 724 vol.2,oct 2001

[18] Wang, L.: Feature Selection with Kernel Class Separability. IEEE Trans. Pattern Anal. Mach. Intell. 30(9), 1534–1546 (2008)