Group-based Relevance Feedback with Support Vector Machine Ensembles

Chu-Hong Hoi and Michael R. Lyu
Department of Computer Science and Engineering
The Chinese University of Hong Kong
Shatin, Hong Kong S.A.R., China
{chhoi,lyu}@cse.cuhk.edu.hk

Abstract

Support vector machines (SVMs) have become one of the most promising techniques for relevance feedback in content-based image retrieval (CBIR). Typical SVM-based relevance feedback techniques simply apply the strict binary classifications: positive (relevant) class and negative (irrelevant) class. However, in a real-world relevance feedback task, it is more reasonable and practical to assume the data come from multiple positive classes and one negative class. In order to formulate an effective relevance feedback algorithm, we propose a novel group-based relevance feedback scheme constructed with the SVM ensembles technique. Experiments are conducted to evaluate the performance of our proposed scheme and the traditional SVM-based relevance feedback technique in CBIR. The experimental results show that our proposed scheme is more effective than the regular method.

1 Introduction

Content-based image retrieval (CBIR) has been widely explored in computer communities in the past decade [1]. In CBIR, relevance feedback was introduced to attack the semantic gap problem existing between low-level features and high-level concepts [2]. It has been shown as a powerful tool to improve the retrieval performance of CBIR systems [2]. In the literature [3, 4, 5], various relevance feedback techniques have been proposed, evolving from earlier heuristic weighting techniques to optimal learning, discriminative learning and classification based techniques [4]. Among the various classification based techniques, Support Vector Machines (SVMs) are considered as one of the most effective techniques for relevance feedback [6, 7].

However, traditional SVM-based relevance feedback techniques normally assume the learning problem as a strict binary classification task. This assumption is not correct in real-world relevance feedback applications. To address this problem, previous studies suggested to represent the relevance feedback as a *(1+x)-class* (one positive class and multiple negative classes) classification problem [8] or *(x+y)-class* (multiple positive classes and multiple negative classes) classification problem [9]. However, in real-world applications, users are more interested in the relevant instances rather than the irrelevant instances. Thus, we suggest to formulate the relevance feedback as an *(x+1)-class* problem. In order to develop an effective algorithm based on our suggested scheme, we proposed to employ the Support Vector Machine ensembles technique to construct our group-based relevance feedback algorithm.

The rest of the paper is organized as follows. Section 2 reviews the background of SVMs. Section 3 discusses the SVM ensembles and the advantages compared with the regular SVM technique. In Section 4, we formulate our group-based relevance feedback algorithm employing the SVM ensembles technique. Section 5 presents the empirical experiments and the retrieval performance evaluation. Section 6 gives the conclusion and future work.

2 Support Vector Machines

As a state-of-the-art classification methodology, SVMs have sound theoretical foundations and provide excellent performance in various pattern recognition applications [10]. The basic idea of SVMs is to look for the optimal decision hyperplane which best separates the data points into two classes with a maximum margin in a projected feature space based on the Structure Risk Minimization principle. For a binary classification problem, given a set of training data points x_i ($i = 1, 2, \ldots, n$), the decision function of an SVM classifier is defined as

$$f(\mathbf{x}) = sign(\sum_{i=1}^{n} \alpha_i y_i K(\mathbf{x_i}, \mathbf{x}) + b) ,$$

where $\mathbf{x}$ is a predicted data point, $y_i \in \{-1, 1\}$ is a class label, $K(\mathbf{x_i}, \mathbf{x})$ is a kernel function for projecting the original data space to a new feature space, n is the number of training samples, α_i and b are the parameters to be solved in the model. The parameters of the optimal decision function can be found by solving the following Quadratic Programming problem:

$$maxL(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j)$$

$$s.t. \quad \sum_{i=1}^{n} \alpha_i y_i = 0 \quad and \quad 0 \leq \alpha_i \leq C, \quad i = 1, \ldots, n \; .$$

The kernel function $K(\cdot, \cdot)$ can have either a linear form or a nonlinear form [10].

3 SVM Ensembles

Although SVMs have been successfully applied in many empirical applications, they have a lot of limitations. First, the regular SVM is originally for binary classification problem. It may not achieve the best performance when applied in multi-class tasks. Moreover, the regular SVM treats fairly with the positive and negative instances. If instances in one of the two-class overnumber another ones, the performance of the regular SVMs may suffer dramatically. To overcome the drawbacks of the regular SVM, the SVM ensemble technique was proposed and have shown promising improvement over the regular SVMs [10, 11].

In general, an SVM ensemble is a collection of several SVM classifiers in which the decision to classify the test data is made by combining the decision functions of all individual classifiers. Suppose there is an SVM ensemble with n individual SVM classifiers, denoted as f_i $(i = 1, 2, \ldots, n)$, and a test data x, the classification result of data x is based on aggregating all the predicting results of n individual SVM classifiers. If all the n individual classifiers are all identical, the classification result is equivalent to each individual classifier. However, if the classifiers are different, the error of prediction can be reduced by combining the n classifiers. Therefore, an ensemble of several individual SVM classifiers is expected to outperform a single SVM classifier.

4 A Group-based Relevance Feedback

4.1 (x+1)-class Assumption

Regular research efforts on relevance feedback simply consider relevance feedback as a two-class classification problem, in which the relevant instances are assumed from one positive class and the irrelevant ones are considered from another negative class. However, in practical applications, the training instances normally come from multiple positive and negative classes. To address this problem, Zhou et al. [8] suggested to represent the relevance feedback as a *(1+x)-class* classification problem (one positive class and multiple negative classes). Nakazato et al. [9] proposed to extend it as an *(x+y)-class* problem (multiple positive classes and multiple negative classes).

However, in relevance feedback tasks, users are more interested in the relevant instances rather than the irrelevant ones. Grouping the relevant instances are easier than classifying the irrelevant ones. Hence, asking the users to group the irrelevant instances is a troublesome and tedious job and it may cost much time for users. Therefore, it is more reasonable to represent the relevance feedback task as an *(x+1)-class* problem (multiple positive classes and one negative class).

4.2 Proposed Architecture

In order to deal with the *(x+1)-class* model, we suggest a novel group-based relevance feedback with the suggested assumption above. On the other hand, we know that the irrelevant instances in the single negative class may overnumber the relevant samples in other positive classes. To attack this problem, we employ the Support Vector Machine Ensembles technique to construct our group-based relevance feedback framework. Fig. 1 depicts our proposed architecture. For the example in Fig. 1, there are two positive groups (PG-1 and PG-2) and a negative group (NG) provided by users. The negative group is divided into two groups based on some sampling strategy. Then the SVM ensemble technique is applied to learn in each positive group. The final retrieval results are obtained by aggregating these two groups.

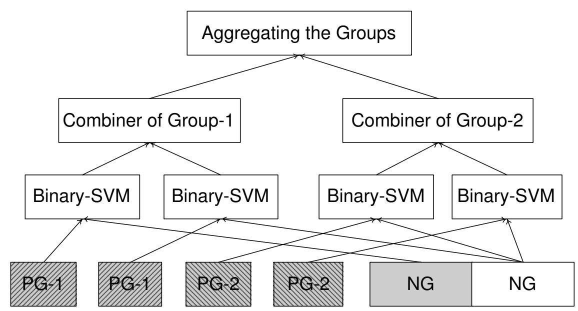


Figure 1. The model architecture of our proposed scheme based on SVM ensembles.

4.3 Combination Strategy for SVM Ensembles

In our group-based relevance feedback algorithm, the combination strategy for an SVM ensemble needs to be addressed. In previous studies of SVM ensembles, a simple strategy is based on majority voting for each class label. When the output of the posteriori probability can be obtained, the sum of the output probabilities is employed to combine the results. Some of other methods incorporate a mixture model of SVMs and other classifiers [12]. However, these previous proposed methods are for pure classification purposes which may not be suitable for retrieval tasks. In order to build algorithms suitable to retrieval tasks, we propose to combine the individual classifiers using the heuristic weighted methods in which the weights of individual SVM classifiers are different. Namely, let f_i (i=1,2,. . .,n) be the decision functions of a set of n individual SVM classifiers, and the weight of each SVM classifier is denoted as w_i $(i = 1, 2, \ldots, n)$. F is denoted as the vector of decision function f_i and W is denoted as the vector of weights w_i. The final decision function of the SVM ensemble is given by

$$f_{\mathrm{SVM.E}}(\mathbf{x}) = W \cdot F,$$

in which the weights of the classifiers are determined by the training data. The decision function is employed for the final retrieval ranking rather than the class predictions in the classification tasks.

5 Experimental Results

5.1 Experiment Implementation

We have implemented a CBIR system to evaluate our proposed group-based relevance feedback algorithm. The graphical user interface (GUI) is shown in Fig. 2. In our relevance feedback mechanism, users drag and group the positive images which are considered as relevant from the retrieval pool in each round. The images remaining in the retrieval pool are considered as irrelevant (negative) in default. The positive images and negative images in the previous round will be accumulated to the next round learning. In our experiments, we compare the retrieval performance

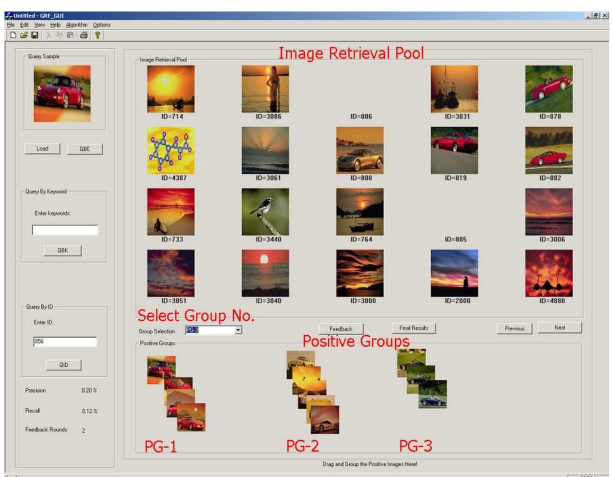
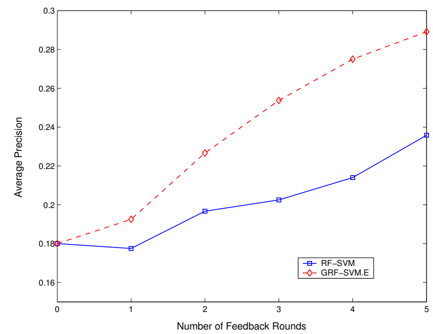


Figure 2. The GUI of Our Group-based Relevance Feedback System.

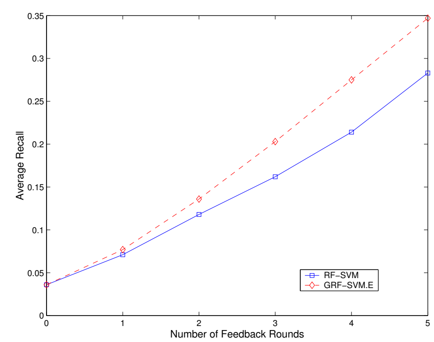
between our proposed group-based relevance feedback with the SVM ensembles (GRF-SVM.E) and the traditional relevance feedback algorithm using SVMs (RF-SVM). The test image dataset used in our experiments is selected from the COREL image datasets. 50 categories of images are selected and each category contains 100 images.

For image representation, three low-level features are extracted: color, shape and texture. Namely, a 36-dimensional low-level feature vector is engaged including a 9-dimensional color moment, an 18-dimensional edge direction histogram and a 9-dimensional wavelet texture feature.

The kernel function for SVM used in our experiments is based on the Radial Basis Function (RBF). We notice that different parameters of the kernel function in SVM have large impact on the retrieval performance. To enable an objective evaluation, the parameters are set to the same constant values for different algorithms respectively.



(a) Average Precision



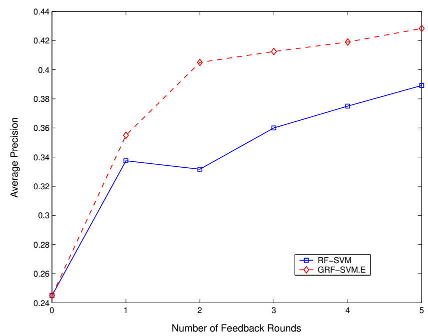
(b) Average Recall

Figure 3. Retrieval Performance for “cars".

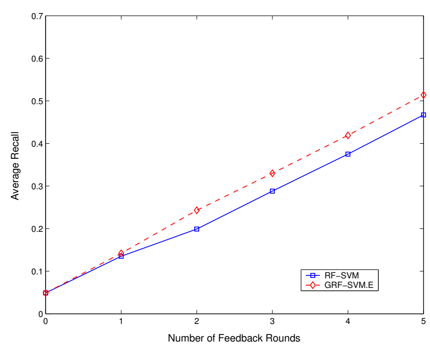
5.2 Performance Evaluation

In the experiments, two semantic concepts are tested to evaluate the retrieval performance. For each concept, 10 testing sessions are engaged. For each testing session, a user first randomly selects a query sample as the initial query point, and then run the relevance feedback algorithm to refine the retrieval results. 5 rounds of feedback are executed in each testing session and 20 images are returned to the user after each round of feedback. In each round, the retrieved results are recorded and compared for different algorithms.

To evaluate the performance, we examine the retrieval precision and recall in the returned images which are the top ranked images in each feedback round. The first evaluated concept is “cars”. Fig. 3 shows the average retrieval precision and recall on the retrieved images for searching the “cars” concept in 5 feedback rounds. From the figures, we



(a) Average Precision



(b) Average Recall

Figure 4. Retrieval Performance for "roses".

can see that the average precision and recall performance of our group-based relevance feedback employing SVM ensembles is better than the regular SVM-based method. And we also observe the similar improvement for searching the "roses" concept from Fig. 4.

6 Conclusion and Future Work

In this paper, we propose a novel group-based relevance feedback scheme in the context of CBIR. Different from traditional approaches, we argue that the relevance feedback task is more reasonable and practical to be represented as an *(x+1)-class* problem. We employ the Support Vector Machine ensembles technique to construct our group-based relevance feedback algorithm. Experiments are conducted to evaluate our suggested scheme. The experimental results demonstrate our proposed scheme is more effective than the regular SVM-based relevance feedback technique.

Although we have already shown some preliminary promising results, a lot of interesting directions can further be investigated in our future work. One direction is to evaluate the performances of various SVM ensembles techniques for attacking the group-based relevance feedback problem. Moreover, we will evaluate our proposed scheme on other larger datasets in the future.

7 Acknowledgement

The work described in this paper was fully supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. CUHK4182/03E).

References

[1] A. W. M. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain, "Content-based image retrieval at the end of the early years," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 22, no. 12, pp. 1349–1380, 2000.

[2] Y. Rui, T. S. Huang, M. Ortega, and S. Mehrotra, "Relevance feedback: A power tool in interactive content-based image retrieval," *IEEE Trans. on Circuits and Systems for Video Technology*, vol. 8, no. 5, pp. 644–655, Sept. 1998.

[3] Y. Rui, T. S. Huang, and S. Mehrotra, "Content-based image retrieval with relevance feedback in mars," in *Proc. IEEE Int. Conf. on Image Processing (ICIP'97)*, Oct. 1997, pp. 815–818.

[4] T. S. Huang and X. S. Zhou, "Image retrieval by relevance feedback: from heuristic weight adjustment to optimal learning methods," in *Proc. IEEE Int. Conf. on Image Processing (ICIP'01)*, Oct. 2001.

[5] T. V. Ashwin, J. Navendu, and S. Ghosal, "Improving image retrieval performance with negative relevance feedback," in *Proc. IEEE Conf. on Acoustics, Speech, and Signal Processing (ICASSP'01)*, Utah, USA, 2001.

[6] P. Hong, Q. Tian, and T. S. Huang, "Incorporate support vector machines to content-based image retrieval with relevant feedback," in *Proc. IEEE Int. Conf. on Image Processing (ICIP'00)*, Vancouver, BC, Canada, 2000.

[7] Simon Tong and Edward Chang, "Support vector machine active learning for image retrieval," in *Proc. ACM Multimedia (MM'01)*, 2001, pp. 107–118.

[8] Xiang Sean Zhou and Thomas S. Huang, "Comparing discriminating transformations and svm for learning during multimedia retrieval," in *Proc. the 9th ACM Multimedia*, 2001, pp. 137–146.

[9] M. Nakazato, C. Dagli, and T. S. Huang, "Evaluating group-based relevance feedback for content-based image retrieval," in *Proc. IEEE Int. Conf. on Image Processing (ICIP'03)*, Spain, 2003, vol. 2, pp. 599–602.

[10] V. N. Vapnik, *The Nature of Statistical Learning Theory*, Springer, New York, 1999.

[11] H.-C. Kim, S. Pang, H.-M. Je, D. Kim, and S. Y. Bang, "Pattern classification using support vector machine ensemble," in *Proc. 16th Int. Conf. on Pattern Recogntion (ICPR'02)*, 2002, pp. 160–163.

[12] R. Yan, Y. Liu, R. Jin, and A. Hauptmann, "On predicting rare class with svm ensemble in scene classification," in *Proc. IEEE Int. Conf. on Acoustics, Speech, and Signal Processing (ICASSP'03)*, 2003.