RELEVANCE FEEDBACK IN CBIR USING THE RLS CLASSIFIER *

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Abstract: The Relevance Feedback has been used to improve the performance of CBIR algorithms. This paper presents a relevance feedback method based on the regularized least squares classifier, and a technique to select feedback information in order to increase the learning rate. Experimental results are presented in the paper to illustrate the performance of the proposed relevance feedback method.

Keywords: *image retrieval, relevance feedback, kernel based classification.*

1 INTRODUCTION

Content Based Image Retrieval (CBIR) systems aim to find sets of relevant images in image databases. This is a difficult task since it is not possible to manually annotate large databases of images by describing their content in terms of keywords. Automatic systems rely on low level image features (e.g., color, texture coefficients). Unfortunately, such systems have a poor performance since low level features are unable to capture semantic concepts e.g., flowers or persons. This problem is known as semantic gap [1]. To overcome this difficulty, the user interacts with the CBIR system by providing additional information during the retrieval process [2]. This is known as relevance feedback.

The first relevance feedback technique presented for CBIR systems was inspired by the work of Rocchio [3] in the context of text retrieval. This technique moves the query point in the direction of the relevant images, giving equal importance to all components of the feature vector. Rui Yong *et al.* [4] extend this technique by assigning different weights to different feature components. Both approaches exhibit poor performance when the distribution of the relevant images in the feature space is multimodal. These difficulties are alleviated by considering multipoint queries [5]. Initially the query is charaterized by a feature vector of one image. After each iteration, a subset of the relevant images is chosen and their feature vectors are added to the query model. The images closer to the multipoint query are retrieved. More recently, several relevance feedback techniques were proposed, based on classification methods [6, 7, 8, 9], which try to classify the database into relevant and non relevant images. Support Vector Machines (SVM) have been extensively used for this purpose [10, 8, 11].

This paper presents an image retrieval system based on relevance feedback. This information is used to interactively build a set of relevant and non relevant images (training set) and to recursively train a binary classifier. This task is performed by the Regularized Least Squares Classifier (RLSC), recently proposed in [12]. This paper also addresses the choice of the images to be evaluated by the user during the retrieval process. We try to combine two conflicting criteria: most relevant and most informative images [6] ranked by RLSC output.

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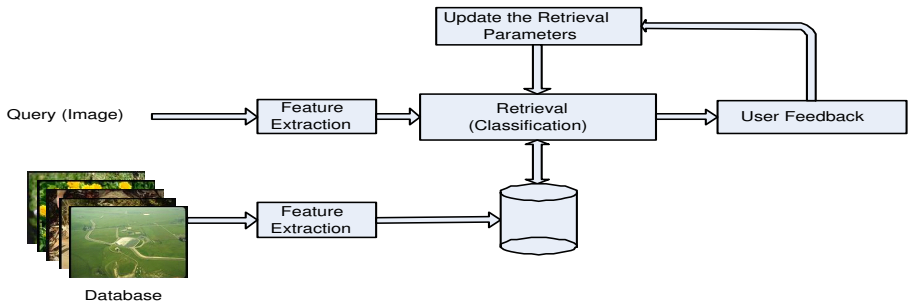


Figure 1: CBIR with Relevance Feedback.

2 SYSTEM OVERVIEW

The system proposed in this paper aims to retrieve images similar to the image query, using the RLS classifier. This is a special classification problem, because most of the data points (image features) are unclassified and only one feature vector (query) is classified as relevant. The training set consists therefore of a single classified vector. Relevance feedback is used to obtain additional information by asking the user to specify the true class of additional images, therefore enlarging the training set in an iterative process (see fig. 1). In each iteration, the system shows the user a set of new images and asks him/her to classify them as positive or negative. The classifier is then retrained and the process repetead. The classifier chosen for this task should have a good generalization capability since the number of classified data points is always a small fraction of the whole database. The main questions to be addressed are:

- How to design a classifier with a small training set of classified patterns?
- How to choose the best images to be classified by the user?

These questions are addressed in sections 3 and 4.

3 CLASSIFICATION USING THE RLSC

This section describes the Regularized Least Squares Classifier used in the relevance feedback algorithm proposed here. Given a training set $S_m = \{(x_i, y_i)_{i=1}^m\}$, where *labels* $y_i \in \{-1, 1\}$, the goal is to estimate the decision boundary between the two classes (relevant/non relevant). The discriminant function used is,

$$f(x) = sign\left(\sum_{i=1}^{m} c_i K(x_i, x)\right), \tag{1}$$

where $K(x, x')$ is the Gaussian kernel, $K(x, x') = e^{-\frac{||x-x'||^2}{2\sigma^2}}$, m is the number of training points and $c = [c_1, ..., c_m]^T$, is a vector of coefficients obtained minimizing the regularized functional [13],

$$\frac{1}{m}\sum_{i=1}^{m}\left[y_i - f\left(x_i\right)\right]^2 + \gamma\left\|f\right\|_k^2, \tag{2}$$

where γ is a positive real number, and $\|f\|_k^2$ is the norm in H_K, reproducing kernel hilbert space, defined by kernel K. The minimization of (2) leads to,

$$c = (m\gamma I + K)^{-1} y, \tag{3}$$

where I is the identity matrix, K is a square positive definite matrix with the elements, $K_{i,j} = K(x_i, x_j,)$ and y is a vector with coordinates y_i.

The points $\{x_i\}$ with, $f(x_i) \leq 0$, are classified in class 2 ($y_i = -1$), and the points with, $f(x_i) > 0$, are classified in class 1 ($y_i = 1$).

4 SELECTING THE BEST POINTS

The selection of display images has an important role in the learning process since it guides the construction of the training set. In this paper a hybrid approach is used to select the set of N points to be displayed in each iteration. The points are selected according to two criteria. First, we select a set of most informative points i.e., points which allow the system to learn the data distribuition and improve the classifier. We also select a subset of points classified as relevant in order to ilustrate the perfomance of the system in each iteration, ranked according to the discriminant function . The set of most informative points is obtained as follows. First, all points in which

$$|f(x_i)| < T, \tag{4}$$

are considered as ambiguous points; T is a threshold defined by the user. Then, all these points are ranked according to the number of neighbours inside a ball of radius R,

$$N_i = |\{x_j : \|x_i - x_j\| < R\}| \qquad i \neq j, \tag{5}$$

The point with highest N_i is chosen and the neighbours inside the ball are all removed. The process is repeated $N/2$ times to select $N/2$ informative points. This strategy allows to obtain information in unexplored regions of the feature space and to perform fine tuning near the decision boundary.

5 EXPERIMENTAL RESULTS

The proposed relevance feedback method was tested using synthetic and real data.

Synthetic data - Gaussian mixtures

The proposed relevance feedback algorithm was tested using a set of feature vectors randomly produced by a mixture of 7 Gaussians with a strong overlap among the Gaussian modes (see fig. 2a). The points generated by two of these Gaussians (25 per cent) were labelled in class 1 (relevant) and the others in class 2 (not relevant). Two points of each class were randomly chosen as seeds to train the RLS classifier.

Figures 2b-d, show the results of the algorithm in three iterations, showing the points classified as relevant (yellow), non relevant (green), ambiguous (red) and the ambiguous points selected (blue crosses). The number of ambiguous points (red) decreases with the iteration number.

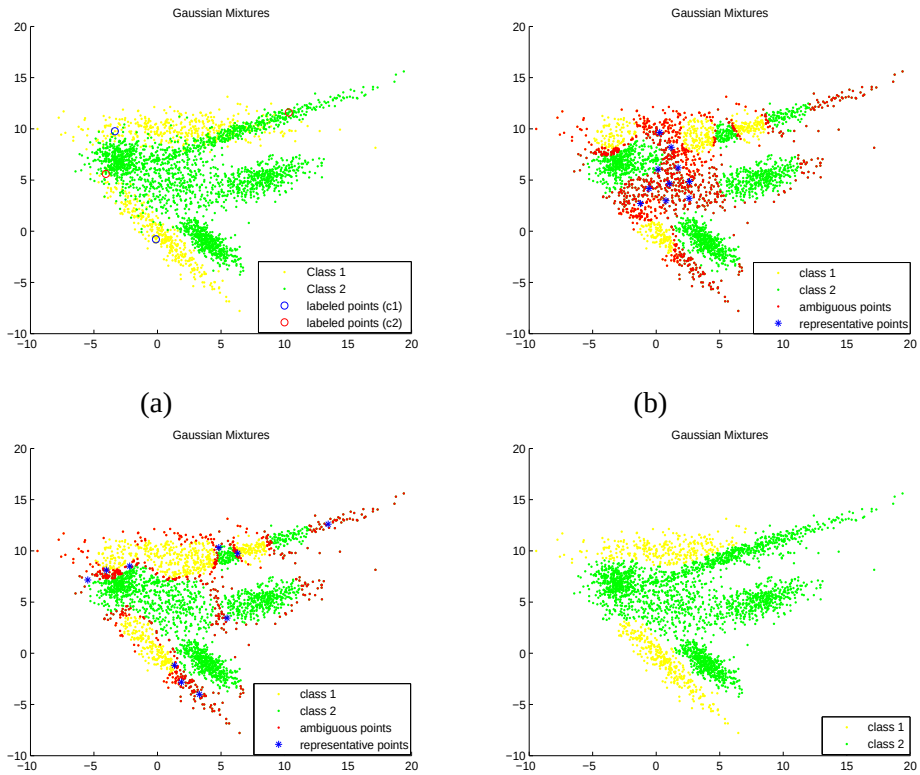
Figure 3, shows the evolution of the error probability which decreases during the experiment. Figure 3a, shows the evolution of the error probability. Each curve is obtained for a different size of the test set. The performance of the proposed algorithm does not change with the increase of the number of unlabelled points. Figure 3b compares two techniques for the selection of display points: the strategy of section 4 and random selection. The proposed method presents better results.

Real data - Images

The proposed system was experimented in a database with 630 images, 530 selected from the UC Berkeley database and 100 images of the CD people II of the Corel stock photo library. These images were divided in 23 classes belonging to 5 groups: sceneries, animals, cars, flowers and people.

In order to evaluate the RF technique proposed, all the images in the database were tested as query and for all of them the precision and recall curves were calculated. The average values of these curves are presented in figures 4a and 4b. Each figure presents a curve with the results obtained without relevance feedback and 2 curves obtained after 3 iterations (14 images per iteration). These 2 curves were obtained using two strategies for the selection of the displayed images: random selection and the method of section 4. Both strategies exhibit a better performance than the system without the relevance feedback. However, the method described in section 4 presents the best performance.

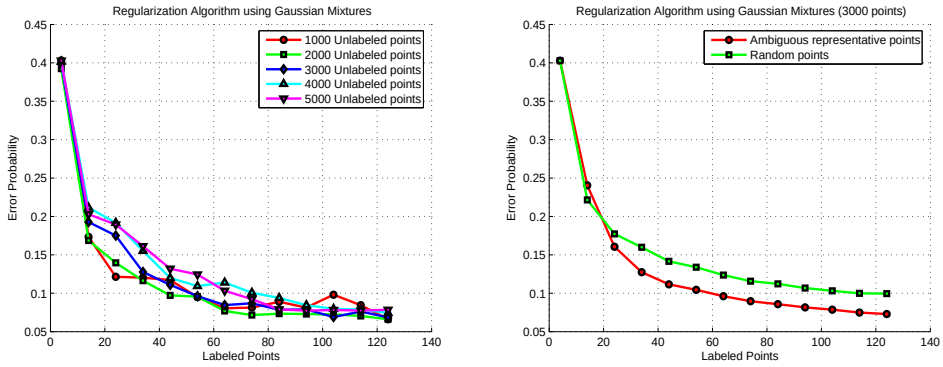
These tests were performed using 14 feedback images in 3 iterations. Similar tests using 10 images in 4 iterations and 20 images in 2 iterations were performed to compare with the first case. Figure 5



(a) (b)

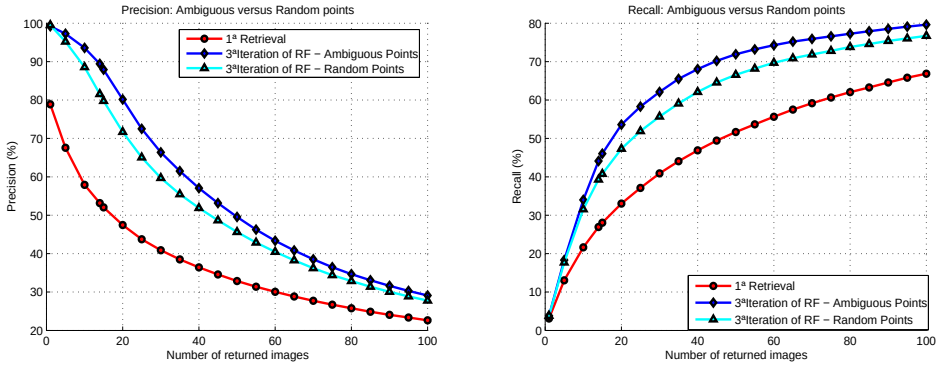
(c) (d)

Figure 2: Performance with synthetic data: a) ground truth; b)c) intermediate results obtained in 2 iterations; d) final results.



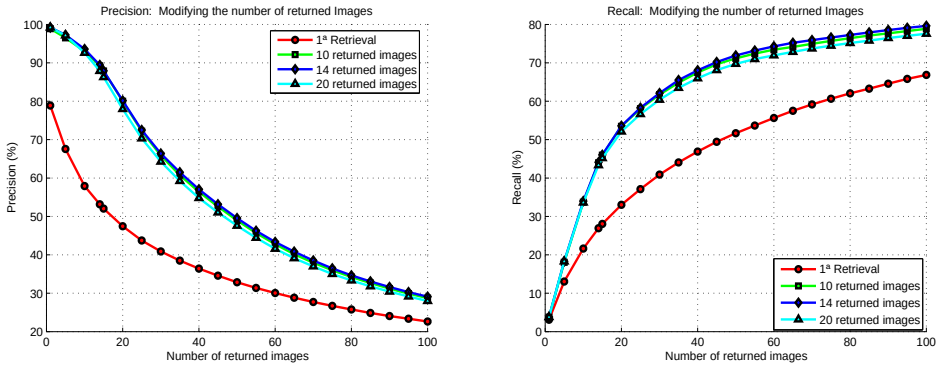
(a) (b)

Figure 3: Evolution of the error probability: a) using a test set with several sizes ; b) selection of the best points method versus random selection.



(a) (b)

Figure 4: Average Precison and Recall obtained by RF algorithm using the best selection points technique versus the random selection.



(a) (b)

Figure 5: Average Precision and Recall obtained by RF algorithm using 10, 14 and 20 images to feedback in each iteration.

and table 1 show the results obtained with these three tests. The three cases present similar results in the final iteration. The second case is more suitable when the user wants results with fewer feedback images. However, if the requeriment is few iterations, the third case is more appropriate. The first case shows a good trade-off between the number of feedback images and the number of iterations.

6 CONCLUSIONS AND FUTURE WORK

This paper presents a system to retrieve images in a database using relevance feedback. The relevance feedback method proposed is based on the Regularized Least Squares classifier and a technique to choose sets of images during the learning process. The relevance feedback algorithm was tested in a database with 630 images and a good performance was obtained with an average precision of 80% and an average recall 54% (20 returned images) after 3 iterations.

In future it will be necessary to test the relevance feedback method with larger databases. Concerning the classifier, it would be useful to devise long-term learning techniques considering information obtained in multiple sessions by multiple users. Finally, the performance of the RLS classifier in the retrieval problem should be compared with other methods namely the Support Vector Machines.

Table 1: Error Probability evolution (average) obtained by the RLS classifier

Iteration	10 images to feedback	14 images to feedback	20 images to feedback
1st	0,43	0,37	0,31
2nd	0,12	0,10	0,07
3rd	0,07	0,06	-
4th	0,05	-	-

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