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Complementary Relevance Feedback Methods for Content-Based Image Retrieval

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1. Introduction

Traditional keyword-based image retrieval (KBIR) is considered a crippled process that suffers the following drawbacks. (1) It is laborious to annotate manually every stored image by keywords selected from a predefined set because modern databases easily contain thousands of images. (2) A real-world image usually involves many concepts, it is difficult to annotate such an image by a small number of keywords. (3) Ambiguities exist between different people's subjects for a given image and would deteriorate retrieval precision when matching the query to the stored images.

Recently, content-based image retrieval (CBIR) (Yoshitaka & Ichikawa, 1999; Smeulders et al., 2000) has emerged as one of the solutions to overcome the limitations entailed by KBIR. Users access CBIR systems (Flickner & Sawhney, 1995; Pentland et al., 1996; Rui et al., 1997; Nastar et al., 1998; Mokhtarian et al., 1996) by directly submitting image examples, object sketches, or other visual information (e.g., color, shape, texture, etc.) The retrievals are ranked based on image processing and similarity matching techniques, alleviating the burden for manual annotations. However, as the ranking of retrievals is calculated according to machine's subject (selected image features), the precision may be unsatisfactory due to the gap between the visual and semantic concepts.

To this end, relevance feedback (RF) treats the retrieval session as repetitive query reformulation operations. Through successive human-computer interactions, the query descriptive information (features, matching models, metrics or any meta-knowledge) is repeatedly modified as a response to the user's feedback on retrieved results. Therefore, the query close to the optimal is eventually produced and the retrieval precision is improved.

Most of the RF approaches for CBIR applications can be classified into three categories. The query vector modification method reformulates the query through user's feedback, so the query is moved towards a region containing more relevant images. The feature relevance estimation approach learns the relevance weight for each image feature and uses the weight to bias the matching. The classification-based method trains a classifier from historic feedbacks for classifying the database images as relevant or irrelevant. Each category of RF methods has its own strengths and weaknesses to be noted in the next section. So it is difficult to design a new RF method which performs best for all kinds of image content. A more practical way is to identify the shared and contrasting features between different RF

methods and design a complementary strategy which maximizes the synergism between multiple RF methods and alleviates the individual weaknesses. In the light of this, we propose a general complementary RF framework which identifies three new RF methods that have proven to be more effective than traditional methods on a real-world image database.
The remainder of this paper is organized as follows. Section 2 reviews the major RF models. Section 3 describes the proposed complementary RF framework. Section 4 presents the experimental results and comparative performances. Finally, conclusions are made in Section 5.

2. Related Work

We begin by describing three major RF models. Then, the comparative strengths and weaknesses between these models are analyzed.

2.1 RF Models

Assume that there are n image items stored in a CBIR database provided for access by many users using the Query_by_example interface. Let Q be the image example submitted by current user and D a database image. Both Q and D are described by r visual features (texture, color, shape, etc.) An option to estimate the visual dissimilarity between Q and D is to compute the Euclidean distance between their visual feature vectors, $\vec{Q} = (q_1, q_2, \ldots, q_r)$ and $\vec{D} = (d_1, d_2, \ldots, d_r)$, as follows.

$$dist_{Euclidean} = \left\|\vec{Q} - \vec{D}\right\| = \sqrt{\left(\vec{Q} - \vec{D}\right) \bullet \left(\vec{Q} - \vec{D}\right)} \tag{1}$$

where the operation $\bullet$ denotes the inner product in the Euclidean space. By deriving the visual dissimilarity between Q and every database image, the retrieval system is able to return a set of v database images that are closest to Q in the visual space. However, owing to the imperfection of feature selection and noise in the feature values, not every returned image is considered relevant by the user. The RF models accommodating user's relevance feedback on the retrieved result can determine a new list of top v similar images to increase the degree of user's satisfaction. Three major RF methods operating in the visual space are reviewed in the following.

- *Query vector modification* (QVM) (Rocchio, 1971; Ciocca & Schettini, 1999) Let R and N denote the subsets of the retrieved result that are marked relevant and irrelevant, respectively, by the user in the incumbent feedback round. QVM reproduces a new query vector by a weighting sum of Q and the mean vectors of R and N. In particular, the new query vector is computed by the following formula.

$$Q \leftarrow \alpha Q + \beta \sum_{D_j \in R} \frac{D_j}{|R|} - \gamma \sum_{D_j \in N} \frac{D_j}{|N|} \tag{2}$$

where Dj is a retrieved image that belongs to R or N, α is the inertia weight promoting the query to move in the same direction as in the previous moving trajectory, and β and γ are the weights controlling the relative importance contributed by relevance and irrelevance experience. The newly produced query vector is then used for searching the next retrievals based on Euclidean metric. QVM has the effect for guiding the reformulation of the query towards relevant images and away from irrelevant ones, and the moving velocity is accelerated by an inertia term considering previous trajectory.

QVM suffers at least the following drawbacks. (1) QVM assumes that each feature is equally relevant to the query; however, the importance of some features may be discounted due to the semantic concept the user is seeking. (2) The parameters α, β and γ need to be empirically tuned in order to perform both effectively and efficiently on databases with various content.

- *Feature relevance estimation* (FRE) (Rui et al., 1998; Peng et al., 1999) The FRE approach assumes that each feature can have a various weight in judging the relevance between Q and D. The appropriate weight of a feature can be learned from the user's incumbent feedback information. A simple notion to estimate the relevance weight of individual feature is the feature projection technique that assesses the retrieval ability (in terms of the number of relevant images retrieved) using each feature alone. Firstly, all the database images are projected onto the axis of the tested feature, so the top s ($\geq v$) closest images to the query with respect to the corresponding feature can be derived. The value of s is at least as large as v because there might be no relevant images in the list of the top v retrieved images using a single feature and little knowledge can be learned. Typically, we set $s = 2v$. Secondly, let Ω_i denote the set of the top s retrieved images using only the ith feature, the relevance weight (w_i) of this feature is apparently related to the number of members of Ω_i that are also in R or N. In general, the relevance weight is estimated by $w_i = f(|R \cap \Omega_i|) - g(|N \cap \Omega_i|)$ where f and g can be linear, quadratic, or exponential functions, depending on the desired learning ratio. Finally, the relevance weights are normalized such that $\sum_{i=1}^{r} w_i = 1$ and they are incorporated into the dissimilarity metric to express the degree of emphasis on the corresponding feature, *viz.*,

$$dist_{FRE} = \left\|\vec{Q} - \vec{D}\right\|_W = \sqrt{\left(\vec{Q} - \vec{D}\right) W \left(\vec{Q} - \vec{D}\right)^T} \quad (3)$$

where W is the feature weight matrix whose diagonal entries are equal to w_i and off-diagonal entries are zero. So $dist_{Euclidean}$ can be viewed as a special case of $dist_{FRE}$ where W is equal to the identity matrix.

Practical applications of FRE also manifest a few shortcomings. (1) The query vector cannot be moved towards a more desired region in the feature space. It is likely that some relevant images may not be selected in the regional neighborhood of the original query. (2) The estimation of relevance weight using the projection technique can be computationally expensive if the feature space involves large dimension.

- *Classification-Based Method* (CBM) (Meilhac & Nastar, 1999; Cox et al., 2000; Tieu & Viola, 2000; Huang et al., 2000; Tong & Chang, 2001; Su et al., 2003; Yin et al., 2008; Li & Hsu, 2008) The CBM approach realizes the retrieval process as a classification task. The collected feedback information (relevant and irrelevant examples) is used as training data such that the employed classifier can be incrementally trained to obtain an improving capability for classification of database images. The popularly used classifiers for image retrieval applications range from Bayes classifier (Meilhac & Nastar, 1999; Cox et al., 2000; Su et al., 2003), to boosting (Tieu & Viola, 2000), graph matching (Li & Hsu, 2008), virtual feature (Yin et al., 2008), and the support vector machine (SVM) (Huang et al., 2000; Tong & Chang, 2001).

Cox et al. (2000) used a Bayesian framework to estimate the *a posteriori* probability that a database image is relevant to the query given the *a priori* probability densities of feature values contributed by the labeled examples from history of feedbacks. Since the probability density function is updated after each feedback round, the system is able to improve the performance of next retrieval. Tieu and Viola (2000) extracted the 20 most relevant features for a given query from more than 45,000 highly selective ones based on the boosting technique. They assumed that relevant images share some visual causes and the learned classifier can focus on a small set of relevant features for a particular query, so the matching is computationally efficient even for a very large database. Huang et al. (2000) incorporated the SVM to determine the preference weight of each positive example collected from the relevance feedback. The farthest positive example from the optimal separating hyperplane (OSH) learned by the SVM receives the highest weight and vice versa. This mechanism releases the user from manually providing the preference weight for each positive example.

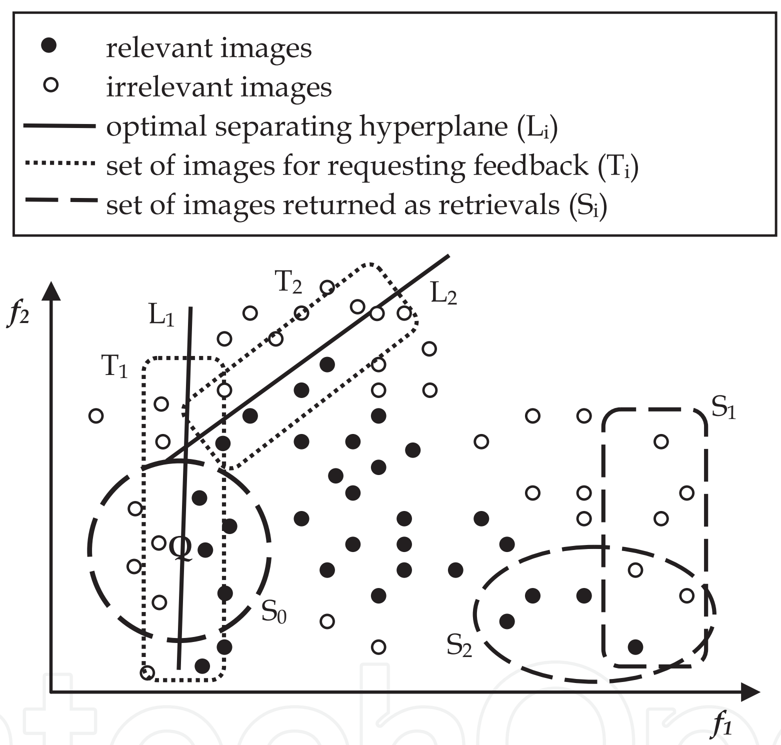


Fig. 1. Illustration of SVM_{Active} method.

Tong and Chang (2001) proposed an SVM active learner (SVM_{Active}) for CBIR with relevance feedback. The database images residing in the farthest places at the positive side from the OSH are returned as current retrievals while the selective images closest to the OSH are shown to the user for providing his/her relevance feedback. Those images marked as relevant or irrelevant are subject to the training of the SVM for next retrievals. So the SVM actively learns from the selective images instead of those randomly presented. The idea of SVM_{Active} method is illustrated in Fig. 1 where two selected features f_1 and f_2 are assumed for simplicity. The zero-page retrievals (S_0) before any relevance feedback are the nearest neighbors of the user-submitted query Q according to the Euclidean distance (Eq. (1)). Based

on the user's feedback regarding to S_0, an SVM is trained and the OSH (L_1) is obtained. The farthest images from the positive side of L_1 are returned as next retrievals (S_1), while the selective images (T_1) closest to L_1 are shown to the user for providing his/her relevance feedback. The SVM is thus trained again using current feedback information and another OSH (L_2) is obtained. The images farthest to L_1 and L_2 are presented as next retrievals (S_2), and the images (T_2) located nearest to L_2 are subject to those asking user's next feedback. Repeating this process, the SVM classifier can be incrementally trained using T_1, T_2, etc. and improves its retrieval performance.
SVM_{Active} method entails the following issues. The SVM treats the retrieval problem as a two-class classification task, when the relevance information is little at the beginning of the query session, the retrieval precision could be very low (see S1 in Fig. 1). The number of false alarms could be great because the number of relevant images is significantly smaller than the number of total images stored in the database. Furthermore, the set of retrieved images is disjoint from the set of images requesting user's feedback. Although this design actively selects the example images that are most useful for the SVM training, it also incurs additional costs for the user to examine two sets of images.

2.2 Comparative Analysis

Our computation experience shows that each RF model imposes individual bias in inferring the image relevance because of its model assumptions. The inference biases of the major RF models are summarized in Table 1. We found that QVM assumes equal relevance weight in similarity matching for each used feature, however, the positive images may be not equally relevant to the query along every feature. The FRE stipulates that the query vector is fixed to the original vector example submitted by the user and will not be reformulated during the query session, so the query vector is incapable of moving to desired regions. The CBM method, on the other hand, treats the retrieval problem as a classification task, the employed classifier could easily impose a great number of false alarms because the number of relevant images is significantly smaller than the number of total images stored in the database.

RF Models	Inference Biases
QVM	● Assume equal relevance weight for each feature, however, the positive images may be not equally relevant to the query along every feature.
FRE	● Query vector is not reformulated, so it cannot be moved towards a more desired region of the feature space.
CBM	● Trained classifier could be severely biased due to insufficiency of training data. The initial performance could be unsatisfactory.

Table 1. Inference biases of major RF models.

Recently, some researchers began studying hybrid methods which provide a chance to improve the performance that can be obtained based on existing RF methods. Yin & Liu (2009) proposed an RF strategy combining QVM and FRE. This strategy moves the query vector to a desired region and simultaneously assigns each feature an appropriate weight of relevance. Yin et al. (2005) proposed a sophisticated framework that automatically chooses the best RF model at a particular feedback round for a given query. They used a reinforcement learning algorithm to maximize the accumulated precision over all submitted queries.

Wang et al. (2003) incorporated the Euclidean search into the SVM active learning in two ways. (1) If an image is classified by the trained SVM as relevant, it is assigned a dissimilarity score equivalent to its Euclidean distance from the known relevant image that is farthest to the OSH. (2) Otherwise, a penalized dissimilarity score is given which is equal to the sum of the distance from the image to the OSH and the maximal distance obtained in (1). Wang's method ensures that an SVM classified negative image would be less preferable than any SVM classified positive image. Moreover, the next included retrievals are the images closest to the known relevant image instead of those farthest to the OSH as employed by the SVM_{Active} method.

3. The Proposed Method

In this section, we propose a general RF framework, named the *complementary method*, which takes advantage of multiple existing RF methods and exploits the synergism between them to improve the performance. We differentiate complementary methods from hybrid methods by the following features. (1) Complementary methods combine two different approaches that are complementary to each other in a hope to eradicate the weaknesses of individual approach, while hybrid methods in general look for a combination scheme of two different methods as long as the overall performance is improved. (2) Complementary methods exploit synergism between two categories of methods, so a general meta-strategy is created and the conception can be implemented in several variations. By contrast, the hybrid methods deal with two carefully selected methods and design all the implementation details instructing how the two methods interweave.

In what follows, we elaborate a complementary RF framework which depicts a general conception for collaborating two types of RF models and identify three effective RF methods.

3.1 Complementary RF Framework

Our complementary RF framework combines two RF models denoted by Θ and Ω where Θ belongs to the classification-based methods (CBM) and Ω could be any alternative method using vector space model or probabilistic model. Fig. 2 shows the conception of the proposed complementary RF framework. Let Q denote the incumbent query submitted by the user. The system fist applies Ω to retrieve a set of v database images that are most similar to Q. These retrievals are presented to the user requesting for relevance feedback. The entered relevant (R) and irrelevant (N) feedback information is exploited in two folds. *First*, the received R and N feedbacks are used to update parameters of the employed RF model Ω, so the retrieval performance is improved. *Second*, the CBM method Θ is incrementally trained by the accumulated set of R and N and the learned classification boundaries become increasingly accurate. All the database images are classified using the trained classifier Θ into two classes: positive (C_1) and negative (C_2) sets. Set C_1 contains those images that are residing at the same side of the classification boundaries as that by the training set R, while C_2 consists of the remaining database images which locate at the other side of the classification boundaries. Set C_2 is filtered out by the system, only set C_1 is used as the image pool for next retrieval performed by the RF model Ω. So Ω is actually working on the set C_1 instead of the whole database. Fig. 3 summarizes the algorithm of the proposed complementary RF framework.

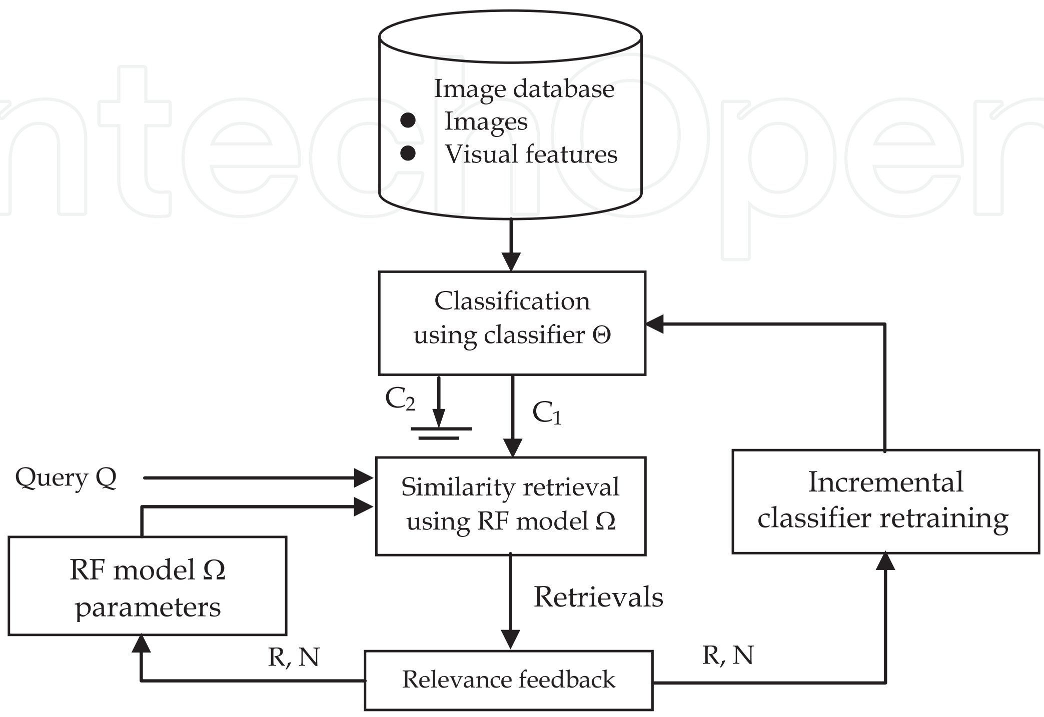


Fig. 2. Conception of the complementary RF framework.

1. Let Q be the current query.
2. Compute v nearest images to Q using the Euclidean distance metric.
3. While user is not satisfied with the currently retrieved result Do
   (a) User marks the v images as relevant or irrelevant.
   (b) Denote by R the set of relevant images, and by N the set of irrelevant images.
   (c) Update the parameters of the RF model Ω using R and N.
   (d) Retrain the classifier Θ using the collective R and N.
   (e) Use Θ to classify the database images into two classes, C_1 (positive class) and C_2 (negative class).
   (f) Retrieve from C_1 the v most similar images to Q using the RF model Ω.

Fig. 3. Algorithmic summary of the complementary RF framework.

The complementary RF framework collaborates Θ and Ω together and maximizes synergism between them. As found in the literature (2003), the CBM method (Θ) usually has low retrieval precision during the first few rounds of relevance feedback. This is due to the fact that the number of relevant images to a query is significantly less than the number of

irrelevant images stored in the database. The classifier Θ easily produces too many false alarms when the training data (user's feedback) are limited at the early feedback period of the query session. But for the same reason, we observed that the negative set produced by Θ are very reliable because the classifier Θ rarely classifies a true relevant image as irrelevant, and this information can be very helpful to another RF model Ω to filter out probable irrelevant images before retrieving. Thus, the proximity for retrieving relevant images using Ω is not constrained to a hyper-sphere or Gaussian neighborhood, but is shaped by the classification boundaries learned by Θ. Moreover, the application of Euclidean-based RF model Ω can avoid producing unsatisfactory precision at the early query session period as encountered by using Θ alone since the retrievals are restrained in the proximity to the reformulated query instead of the farthest positive images to the classification boundaries.
In the following, we identify three implementations of the complementary RF framework that empirically prove to be effective in our experiments.

3.1.1 SVM-complementing QVM

The SVM-complementing QVM (SVM^cQVM) uses SVM as the classifier Θ and QVM as the RF model Ω. As previously noted, QVM reformulates the query vector by reference to the feedback information and intends to move the query vector towards a region containing more relevant images. However, QVM does not produce a classification boundary optimally separating the feedback data and, therefore, the next retrievals in the proximity to the reformulated query may include some undesired images that should have been ruled out by carefully exploiting the feedback data. This phenomenon is shown in Fig. 4 where Fig. 4(a) illustrates the retrieving process using QVM and Fig. 4(b) corresponds to the retrieving process using SVM^cQVM. It is observed from Fig. 4(a) that QVM reformulates the original query Q_0 based on feedback information contained in S_0 to generate a new query Q_1, so the images in the proximity to Q_1 are returned as new retrievals (S_1). However, some irrelevant images are also contained in S_1 and deteriorate the retrieval precision. On the other hand, as shown in Fig. 4(b), SVM^cQVM can improve retrievals by learning a classification boundary (L_1) using the feedback information contained in S_0. The images residing at the same side of L_1 as that by the previously retrieved irrelevant images (denoted by "–") are filtered out by the SVM classifier, the proximity S_1 thus extends to seduce more potential images as retrievals that are not reachable using the traditional QVM. Also, the proximity S_1 of the reformulated query Q_1 is not constrained to a spherical neighborhood, but is shaped by the classification boundary. As the system proceeds with more feedback rounds, the classification boundary learned by the SVM classifier would be more accurate (see Fig. 1), hence, the improving on the retrievals is remarkable.

3.1.2 SVM-complementing FRE

The SVM-complementing FRE (SVM^cFRE) uses SVM as the classifier Θ and FRE as the RF model Ω. As shown in Fig. 5(a), the traditional FRE estimates the feature relevance weights by feature projection of the feedbacks and incorporates the weights into the Euclidean metric. So the proximity (S_0) to the query Q is reformed to an elliptical neighborhood (S_1) to search more potentially relevant images. Analogous to the case of using traditional QVM, FRE does not produce a classification boundary from the feedback data and could invite irrelevant retrievals that are likely to be easily screened by the SVM classifier Θ.

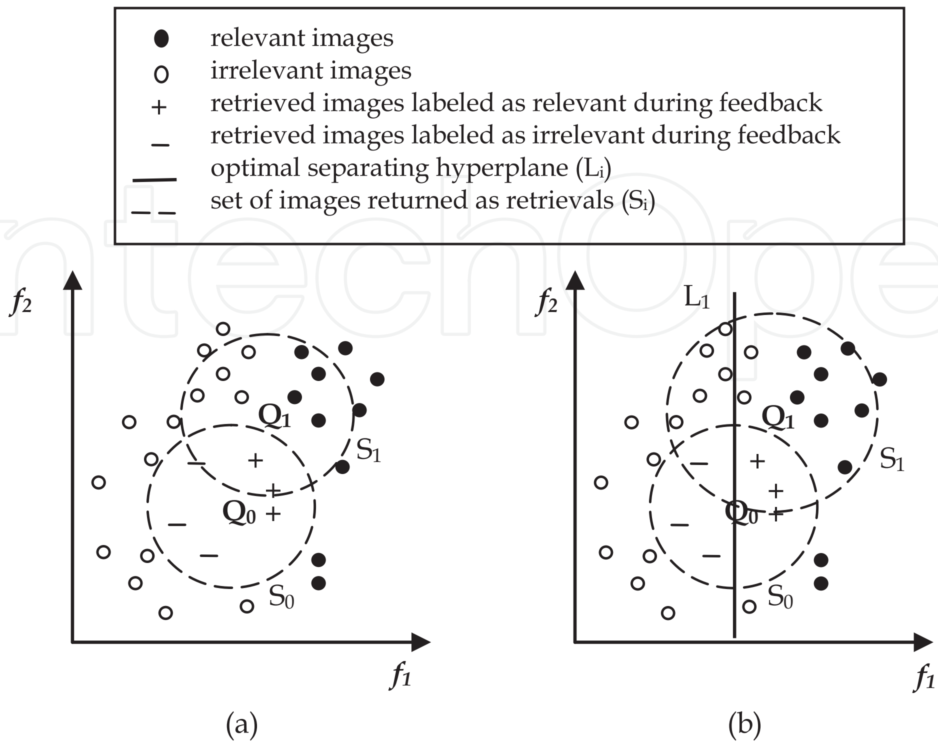


Fig. 4. Comparison between QVM and SVM^{c}QVM methods.

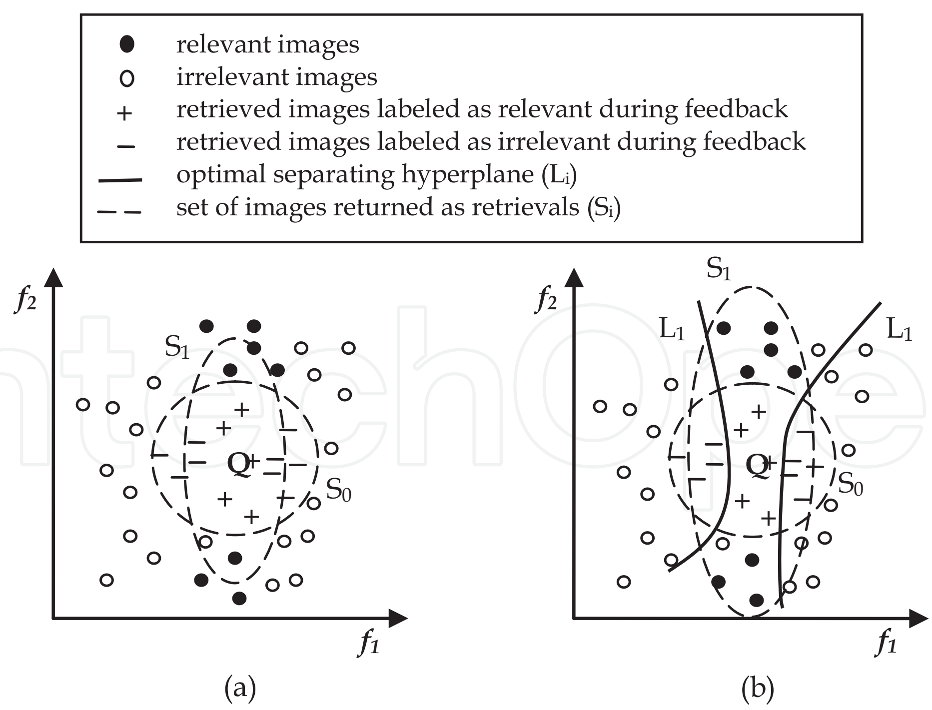
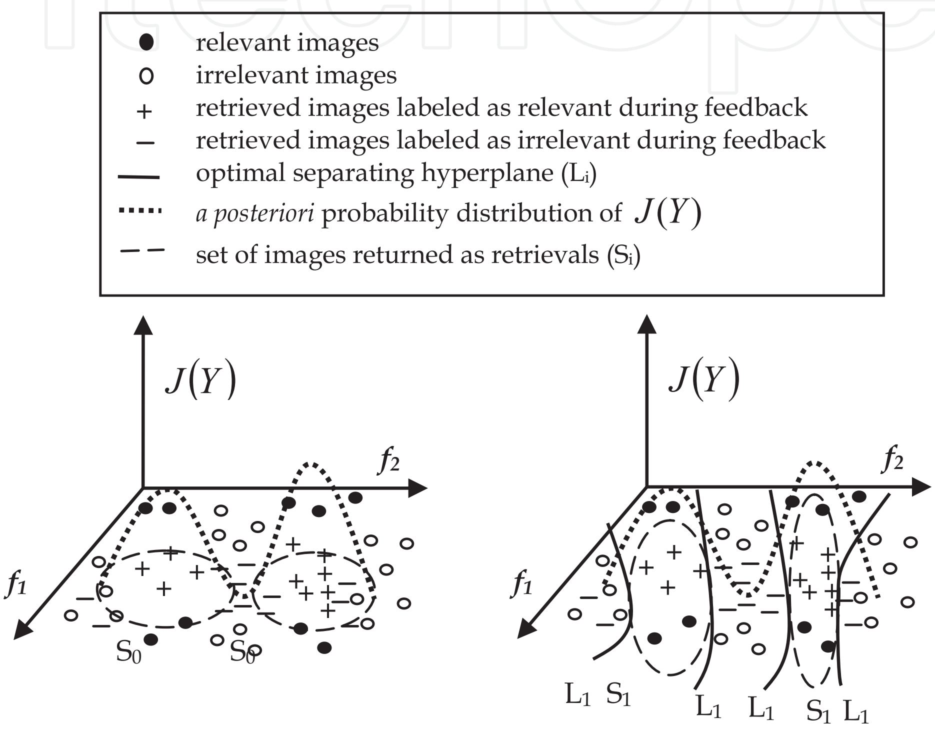


Fig. 5. Comparison between FRE and SVM^{c}FRE methods.

Using the SVM^cFRE approach, it is seen from Fig. 5(b) that SVM^cFRE learns the classification boundaries (L_1) separating the feedback data labeled as relevant ("+") and irrelevant ("–"). The boundaries help FRE to filter out the images residing at the same side of L_1 as that by the labeled irrelevant images, so the proximity S_1 can further extend to promising area containing potentially relevant images that are however not reachable by traditional FRE.

3.1.3 SVM-complementing Bayes



(a) (b)

Fig. 6. Comparison between Bayes and SVM^cBayes methods.

The SVM-complementing Bayes (SVM^cBayes) uses SVM as the classifier Θ and a Bayes framework (Cox et al., 200) as the RF model Ω. The Bayesian framework estimates the *a posteriori* probability that a given image Y is relevant ($p(R|Y)$) or irrelevant ($p(N|Y)$), and they are computed by $p(R|Y) = p(Y|R)p(R)/p(Y)$ and $p(N|Y) = p(Y|N)p(N)/p(Y)$ where conditional probabilities $p(Y|R)$ and $p(Y|N)$ can be approximated by parametric models such as Gaussian kernels using the feedback information R and N, $p(R)/p(N)$ is a small constant for a given query Q since the number of relevant images is much less than that of irrelevant images. Then, the Bayesian framework retrieves the top v images with the highest values of $J(Y) = p(R|Y)/p(N|Y) = p(Y|R)p(R)/p(Y|N)p(N)$. Fig. 6(a) illustrates the distribution of $J(Y)$ using Bayesian framework.

To complement Bayesian framework which relies on probability densities of feedback data, SVM extracts the support vectors from the feedback information and learns the classification boundaries that maximize the margin from the boundaries to the support vectors. Fig. 6(b) gives the retrieving process using SVM^cBayes. It is observed that the classification boundaries (L_1) learned by SVM separate the labeled relevant and irrelevant data without considering their distributions and help the Bayesian framework invite potentially relevant images with relatively low values of $J(Y)$ that are originally not of interest.

4. Experimental Results

We have implemented the major RF models in the literature including QVM (Ciocca & Schettini, 1999), FRE (Peng et al., 1999), Bayes (Cox et al., 2000), and SVM_{Active} (Tong & Chang, 2001), and the proposed complementary RF methods, namely SVM^cQVM, SVM^cFRE, and SVM^cBayes. The parameter values of the exiting methods follow the suggested values from their original papers. A real-world image database is used for performance evaluation.

4.1 Testing Database and Performance Measure

To testify the robustness and effectiveness of our complementary RF framework, the experiments have been conducted on a real-world image database (UCR database, 2008) containing 2,026 images classified into 19 topics such as ocean, forest, buildings, cars, humans, animals, etc. The sample images from each topic are shown in Fig. 7. To evaluate the retrieval performance of competing methods, the images from the same topic are considered relevant and the images from different topics are deemed irrelevant, so the retrieval precision obtained at different rounds of feedback can be computed automatically. The features used for image matching in our experiments consist of 22 visual features, namely, 16 Gabor features (mean and standard deviation of Gabor images at 4 orientation and 2 scales) and 6 color features (mean and standard deviation from the HSV color domain).

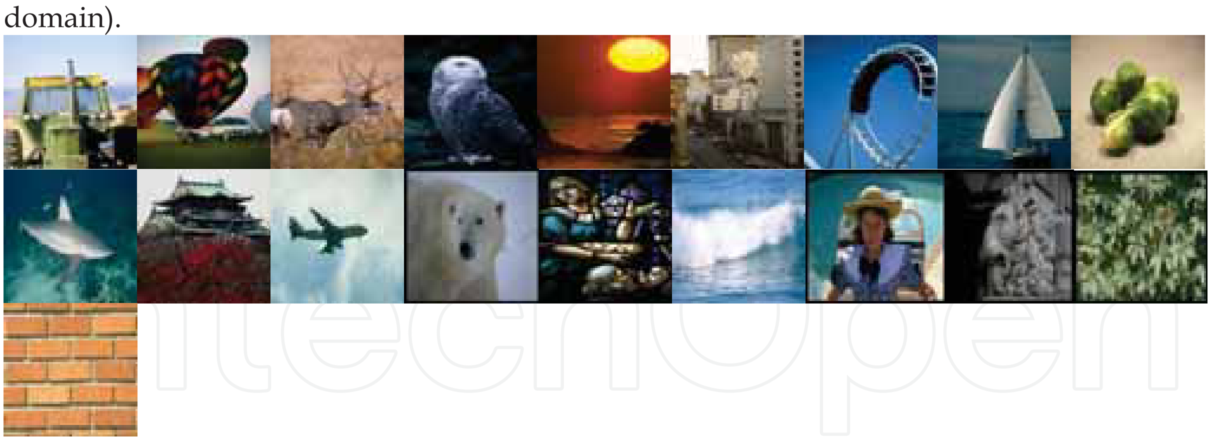


Fig. 7. Sample images from the 19 topics of the testing database.

We use the *Average Precision* (AP) measure defined by NIST TREC video (TRECVID) in our experiment for performance evaluation. Each database image is presented as a query and proceeds with 10 rounds of feedback. The feedback is automatically executed by reference to the 19 topics. The AP value that can be obtained at each round is defined as the average of precision value obtained after each relevant image is retrieved. The precision value is the ratio between the retrieved relevant images and the number of images currently retrieved.

Let $\overline{P}$ be the AP obtained at the current round of feedback and it is computed by $\overline{P} = \sum_{D_i \in R} P_i / |R|$ where P_i denotes the precision value obtained after the system retrieves i relevant images, D_i is one of the relevant images, R is the set of all relevant images that belong to the same topic as the query, and $|R|$ denotes the cardinality of R. As an example, assume one of the topics consists of six relevant images and the retrieval system ranks these relevant images at the first, second, fourth, seventh, thirteenth, and eighteenth places. Thus, the precision value obtained when each relevant image is retrieved is 1, 1, 0.75, 0.57, 0.38, and 0.33, respectively. The AP computes the average of these precision values and it is 0.67. The AP calculated over all relevant images can avoid precision fluctuation that is usually encountered by the traditional precision measure.

4.2 Comparative Performance Evaluation

In this section, we compare the complementary RF method with its counterparts by submitting each of the 2,026 database images as a query and compute the average AP obtained at various numbers of feedback rounds. Fig. 8 shows the average AP obtained by SVM^{c}QVM and its related methods, the individual SVM$_{Active}$ and QVM. We observe that SVM$_{Active}$ performs relatively worse during the first three rounds because it does not rely on the Euclidean-based proximity to the query. Instead, SVM$_{Active}$ retrieves the farthest images to the optimal separating hyperplane (OSH) and could result in low precision when the training feedback data are limited. When the system experiences more than three rounds of feedback, SVM$_{Active}$ becomes more effective and the average AP increases quickly. On the other hand, QVM is effective at the first few rounds of feedback since it progressively predicts the promising region adjacent to the centroid of known relevant images, and moves the reformulated query to that region. But its performance is constrained by the assumption that the retrievals are located in a spherical-shaped proximity to the reformulated query.

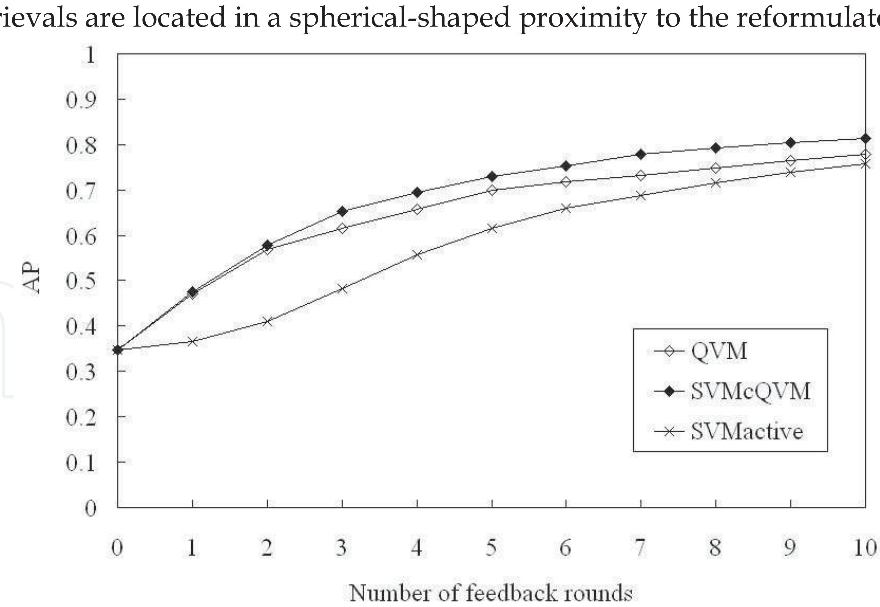


Fig. 8. The average AP obtained by QVM, SVM^{c}QVM, and SVM$_{Active}$ at different numbers of feedback rounds.

By complementing the two methods, SVM^{c}QVM filters out highly possible irrelevant images and shapes the retrieval neighborhood for QVM by the classification boundaries learned by SVM$_{Active}$. In essence, the retrieval neighborhood used for SVM^{c}QVM is no longer constrained by a hyper-sphere and can take any forms of shape. Further, as SVM^{c}QVM applies the query reformulation and locates the most promising region, so it avoids the suffering of inferior performance at early feedback rounds as encountered by SVM$_{Active}$. It is seen from Fig. 8 that SVM^{c}QVM attains the best performance among the compared methods, manifesting the synergistic effect between SVM$_{Active}$ and QVM.

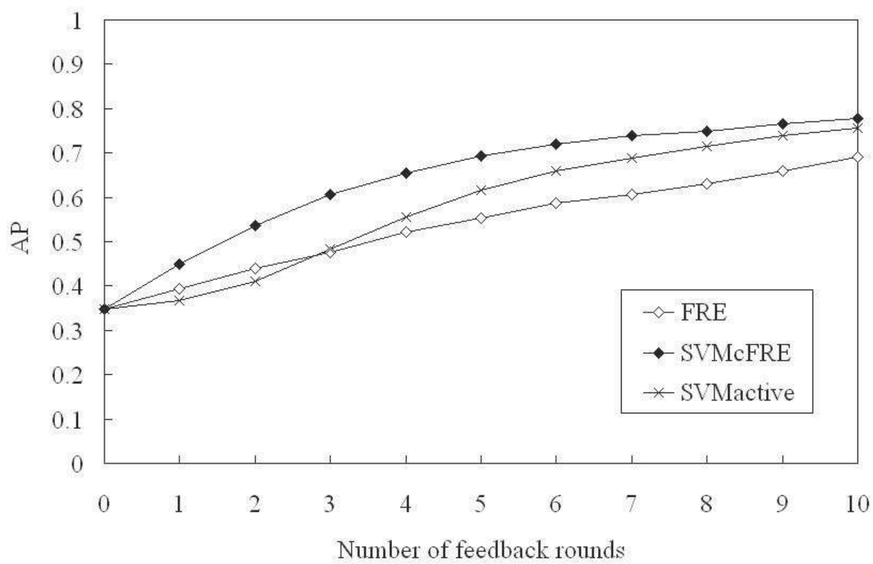


Fig. 9. The average AP obtained by FRE, SVM^{c}FRE, and SVM$_{Active}$ at different numbers of feedback rounds.

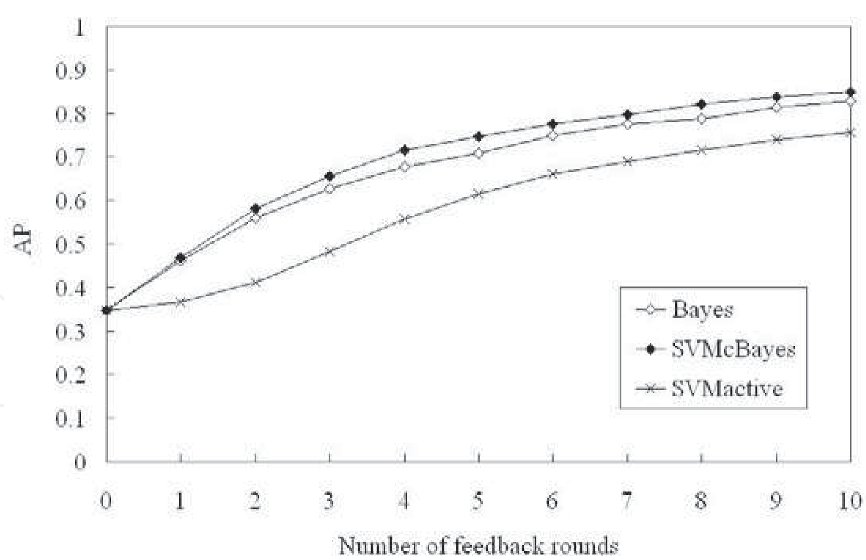


Fig. 10. The average AP obtained by Bayes, SVM^{c}Bayes, and SVM$_{Active}$ at different numbers of feedback rounds.

Figs. 9 and 10 show the comparative performances obtained using SVM^{c}FRE, SVM^{c}Bayes and their counterparts, respectively. Similar phenomena are observed in these figures. The complementary RF methods always outperform their counterparts at every round of feedback. This means that the proposed complementary RF framework is general and can be applied to a broad range of existing RF methods. By contrast, the traditional ad-hoc hybrid method specifically sticks to the combination components and is hard to be applied to other components. The complementary RF framework is in fact a meta-strategy that guides the search of embedded models to maximize their synergism by exploiting the complementarity between them.

4.3 Retrieval Examples

Here, we present visual results of some retrieval examples using competing methods. Fig. 11(a) shows the zero-page retrieval results before performing any relevance feedback. The query example image is shown at the top of the figure. The retrieved images are ranked according to their Euclidean distances to the query and *seven* of them belong to the same topic as the query, obtaining a precision value of 35%. By marking the retrieved images as relevant or irrelevant, we obtain various next retrieval results with different degrees of precision improving. The traditional QVM, FRE, and Bayes are able to assist the system to locate ten, seven, and nine relevant images in the new retrievals, respectively, as shown in Figs. 11(b)-11(d). However, it is seen in Fig. 11(e) that SVM_{Active} only find three relevant images after the first feedback round because SVM_{Active} searches the farthest positive images to the OSH instead of the closest images to the reformulated query, this mechanism is not effective when the feedback information is little, as most of other machine learning algorithms suffer this limitation as well. By contrast, our proposed complementary RF methods, namely, SVM^cQVM, SVM^cFRE, and SVM^cBayes are very effective in utilizing the relevance feedback, obtaining 12, 13, and 12 relevant images, respectively, as seen in Figs. 11(f)-11(h). The results exhibit a significant performance improving on their combining components. This remarkable contribution should be dedicated to the filtering of highly-possible irrelevant images, the classification boundaries learned by SVM shape the similarity neighborhood used by QVM, FRE, and Bayes more accurately.

The synergistic effect produced by our complementary methods is more profound after the second round of relevance feedback. As shown in Figs. 12(a)-12(d), QVM, FRE, Bayes, and SVM_{Active} improve the retrievals by finding 13, 10, 12, and 15 relevant images, compared to just locating 10, 7, 9, and 3 relevant images in the results obtained in the first round. It is noteworthy that SVM_{Active}, although less effective in the first round, surpasses QVM, FRE, and Bayes in the second round because the volume of feedback information is increasing and the learned classification boundaries are more accurate. This also enhances the filtering capability of complementary methods. We observe from Figs. 12(e)-12(g) that SVM^cQVM, SVM^cFRE, and SVM^cBayes find 17, 16, and 17 relevant images in the second feedback round, revealing the synergism between the combining components is being maximized.

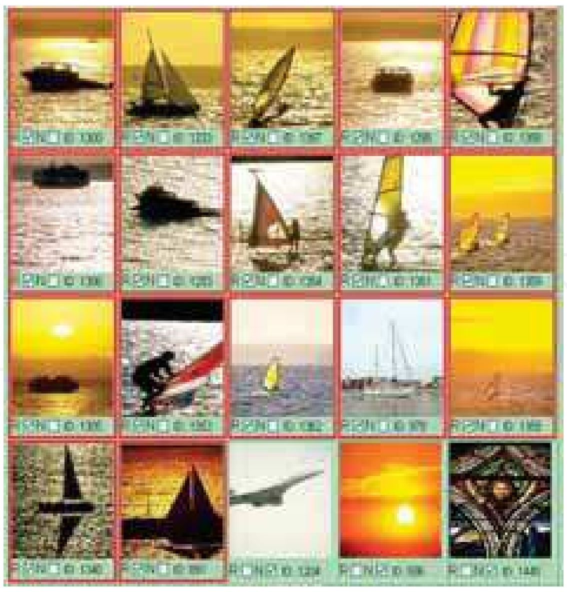
Table 2 summarizes the retrieval results obtained using the competing methods at different rounds of relevance feedback. Clearly, our complementary methods can enhance the retrieval capability of combining methods at all rounds of relevance feedback.

Fig. 11. Visual results of some retrieval examples in the zero-page and the first feedback round using competing methods.

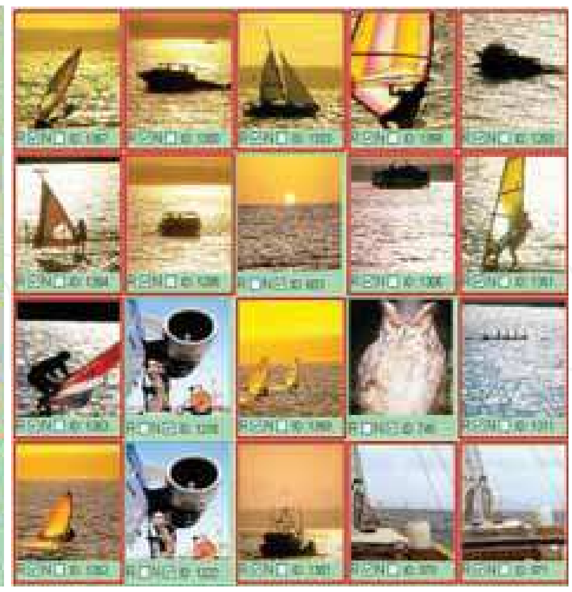
(e) (f) (g) (h)

Fig. 11. Visual results of some retrieval examples in the zero-page and the first feedback round using competing methods (continued.)

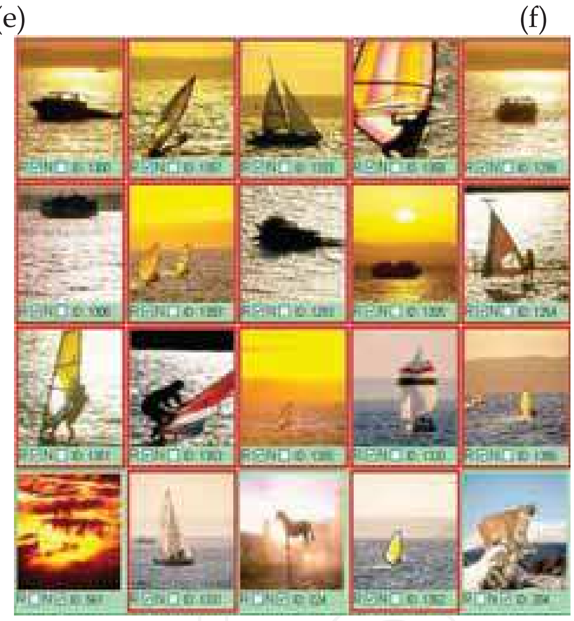
Fig. 12. Visual results of some retrieval examples in the second feedback round using competing methods.



(e)



(f)



(g)

Fig. 12. Visual results of some retrieval examples in the second feedback round using competing methods (continued.)

	QVM	FRE	Bayes	SVM$_{Active}$	SVM^{c}QVM	SVM^{c}FRE	SVM^{c}Bayes
1st round	10	7	9	3	12	13	12
2nd round	13	10	12	15	17	16	17

Table 2. Retrieval results obtained using the competing methods at different rounds of relevance feedback.

5. Conclusions

Our recent survey on previous relevance feedback (RF) approaches disclosed that each type of RF methods has its own strengths and weaknesses, and that there is no RF method which performs best for all kinds of image content. We thus have proposed an innovation for the design of complementary methods which exploit the complementarity between different types of RF methods and create a meta-strategy that maximizes the synergism by guiding the collaboration between the combining RF methods. In particular, we have identified three implementations of the complementary methods, namely, the $SVM^{c}QVM$, $SVM^{c}FRE$, and $SVM^{c}Bayes$. These methods not only essentially avoid the inferior performance during early period of query session as suffered by SVM_{Active}, but also shape the retrieval proximity to the reformulated query by classification boundaries, relaxing the restriction to hyper-spherical or Gaussian neighborhoods as faced by QVM, FRE, and Bayes. Experimental results obtained by testing on a real-world image database manifest that the proposed complementary methods outperform their original counterparts and the improving on retrievals is significant.

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For more than 40 years, pattern recognition approaches are continuingly improving and have been used in an increasing number of areas with great success. This book discloses recent advances and new ideas in approaches and applications for pattern recognition. The 30 chapters selected in this book cover the major topics in pattern recognition. These chapters propose state-of-the-art approaches and cutting-edge research results. I could not thank enough to the contributions of the authors. This book would not have been possible without their support.