Journal of Information Hiding and Multimedia Signal Processing ©2018 ISSN 2073-4212
Ubiquitous International Volume **9**, Number **1**, January **2018**

A Review on Relevance Feedback for Content-based Image Retrieval

Dongping Tian

Institute of Computer Software
Baoji University of Arts and Sciences
No.1 Hi-Tech Avenue, Hi-Tech District, Baoji, Shaanxi 721013, P.R. China

Institute of Computational Information Science
Baoji University of Arts and Sciences
No.44 Baoguang Road, Weibin District, Baoji, Shaanxi 721007, P.R. China
tiandp@ics.ict.ac.cn, tdp211@163.com

Received August, 2017; revised October, 2017

Abstract. *Content-based image retrieval (CBIR) has been an active topic of research in computer vision for decades. Due to the existence of semantic gap, much research has also been devoted in the past few years to relevance feedback as an effective solution to improve the performance of CBIR systems. Compared with various relevance feedback approaches and their corresponding applications within the content-based image retrieval community, little attention has been paid to its summary researches. So this paper provides a comprehensive review on relevance feedback for CBIR. To start with, the basic principle of relevance feedback is introduced. Subsequently, the relevance feedback for CBIR is elaborated from three aspects of query-point movement, feature re-weighting and Bayesian method, respectively. Finally, the paper is ended with a summary of some important conclusions and potential research directions of relevance feedback for content-based image retrieval in the future.*
Keywords: Relevance feedback, CBIR, Semantic gap, Bayesian estimation, Region-based image retrieval

1. **Introduction.** With the explosive growth in image records and the rapid increase of computer power, retrieving images from a large-scale image database has become one of the most active research fields in recent years. Content-based image retrieval (CBIR) is a technique to retrieve images semantically relevant to the users query from an image database. However, the semantic gap between low-level image features and high-level semantic concepts is a major obstacle to image retrieval related tasks. To improve the retrieval performance, more research efforts have been shifted to the relevance feedback (RF) so as to obtain efficient CBIR systems. As a powerful tool to boost the retrieval performance in content-based image retrieval systems, RF works by gathering semantic information from user interaction. The user labels each image returned in the previous query round as relevant or non-relevant (or a range of values). Based on this feedback, the retrieval scheme is adjusted and the next set of images is presented to the user for labeling. From the literature, it can be easily observed that a variety of relevance feedback techniques have been proposed, evolving from earlier heuristic weighting technique to optimal learning, discriminative learning and classification-based techniques [1]. In general, most of

these relevance feedback strategies can be roughly classified into three categories: query-point movement, feature re-weighting and Bayesian method [2]. Compared with various RF approaches and their corresponding applications in the content-based image retrieval community, there are just very few review researches on the relevance feedback. So in this paper, we focus our review on the relevance feedback techniques so as to complement the existing surveys in the literature.

The rest of this paper is organized as follows. Section 2 briefly describes the basic principle of relevance feedback. In section 3, RF procedure is elaborated from three aspects, including query-point movement, feature re-weighting and Bayesian method, respectively. Section 4 summarizes other relevance feedback strategies for CBIR. Finally, this paper is ended with a summary of some important conclusions and potential research directions of relevance feedback for content-based image retrieval in the future.

2. **Relevance Feedback.** Relevance feedback, originally developed for information retrieval, is an online learning technique used to improve the effectiveness of information retrieval systems through iterative feedback and query refinement. RF is introduced into CBIR during the early and mid-1990s, with the intention to bring user in the retrieval loop to reduce the semantic gap between what queries represent and what the user thinks. By continuous learning through interaction with end-users, RF has been shown to provide dramatic performance boost in image retrieval systems [3]. In a word, the basic idea of RF is to let users guide the system. During retrieval process, the user interacts with the system and rates the relevance of the retrieved images according to his subjective judgment. With this additional information, the retrieval system can dynamically learn the users intention and gradually present better results. RF has been introduced into image retrieval to primarily address two questions referring to the CBIR process. One is the semantic gap between high-level visual properties of images and low-level features extracted to describe them. Another issue is concerned with the subjectivity of the image perception due to different people may have distinct visual perceptions of a same image. Fig. 1 illustrates a simple diagram of a CBIR system with relevance feedback.

A typical scenario for relevance feedback in CBIR can be described as follows:

Step 1: *Machine provides an initial retrieval results, through query-by-example, sketch, etc.*

Step 2: *User provides a judgment on the currently displayed images as to whether and to what degree, they are relevant or irrelevant to the query.*

Step 3: *Machine learns and tries again. Go to step 2.*

Note that steps 2-3 need to be repeated until the user is satisfied with the retrieval results.

3. **Relevance Feedback for CBIR.** Basically, relevance feedback strategy is motivated by the observation that the user is unaware of the image distribution in feature space, nor of the feature space itself, nor of the similarity metric. So RF techniques proposed in the literature involve the optimization of one or more CBIR components, such as the formulation of a new query and/or the modification of the similarity metric to take into account the relevance of each feature to the user query, etc. In recent years, many relevance feedback techniques have been proposed and most of them can be roughly classified into three categories: query-point movement (QPM), feature re-weighting and Bayesian method [2]. In QPM, the components of the query vector were updated using the average of component values of all relevant samples and all non-relevant samples so that the new query point moved towards the centre of relevant class and away from non-relevant class. The essence of feature re-weighting was to put more weights on the feature components

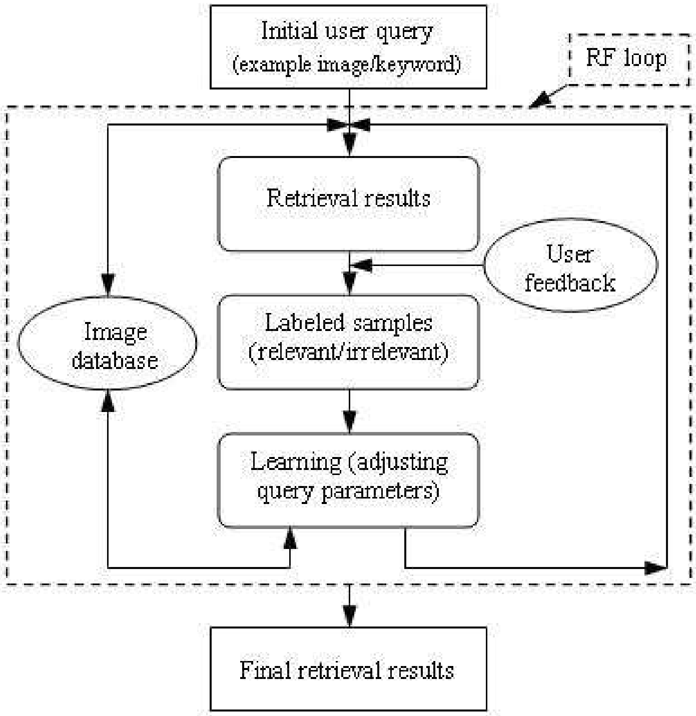

FIGURE 1. CBIR system with relevance feedback

those were more important in discriminating between relevant and non-relevant images and thus, enhancing retrieval. It was found to be very suitable for large size databases and high dimensional feature space [4]. Also, this method was simple to implement and produced fairly good retrieval. As for the Bayesian method, which estimated the probability of a database image being relevant to the query and updated it with iteration [5,6]. Even if this approach was theoretically sound as it did not rely on the nearest-neighbor search, it was computationally intensive. In the following, a comprehensive review of RF related studies will be described based on the RF strategies aforementioned for image retrieval, respectively. Note that Table 1 summarizes the characteristics of relevance feedback for CBIR.

3.1. **Query-point movement for CBIR.** The method of the query-point movement approach was to construct a new query point that was supposed to be close to the relevant results and far from those that were non-relevant. In other words, the QPM method essentially tried to improve the estimate of the "ideal query point" by moving it toward good examples point and away from bad example points. The best-known approach, initially developed by Rocchio in the context of textual information retrieval, to achieve QPM was based on the following formula for sets of relevant documents D_R and non-relevant documents D_N given by the user:

$$Q' = \alpha Q + \beta\left(\frac{1}{N_{R'}}\sum_{i\in D_R} D_i\right) - \gamma\left(\frac{1}{N_{N'}}\sum_{i\in D_N} D_i\right) \tag{1}$$

Table 1. Summary of the characteristics of relevance feedback for CBIR

Purpose	Augment keyword retrieval: query reformulation give user opportunity to refine their query tailored to individual exemplar based − different type of information from the query iterative, subjective improvement Evaluation
Examples	Image Retrieval http://www.cs.bu.edu/groups/ivc/ImageRover/ http://nayana.ece.ucsb.edu/imsearch/imsearch.htm http://www.mmdb.ece.ucsb.edu/∼demo/corelacm/
Early Usage	Modify original keyword query strengthen terms in relevant docs weaken terms in non-relevant docs modify original query by weighting based on amount of feedback
Early Results	Evaluation: how much feedback needed how did recall/precision change Conclusion: improved recall/precision over even 1 iteration & return of up to 20 non-relevant docs Promising technique

where Q and Q' were the original query and updated query respectively, D_R and D_N denoted the positive and negative samples returned by the user, $N_{R'}$ and $N_{N'}$ were the number of samples in D_R and D_N, respectively, α, β and γ were selected constants.

As far as the application of QPM in image retrieval community was concerned, Lu et al. [7] presented a framework by seamlessly integrating both semantics and low-level features into the relevance feedback process, which took advantage of the semantic contents of images in addition to low-level features. By forming a semantic network on top of the keyword association on the images, it was able to accurately deduce and utilize the image's semantic contents for retrieval purposes. Moreover, a ranking measure that integrated both semantic- and feature-based similarities for this framework was constructed as below. Fig. 2 illustrates the proposed framework. It supports both query by keyword and query by image example through semantic network and low-level feature indexing.

In the meanwhile, a system was constructed to integrate the region-based representations and relevance feedback by [8], in which both the query-point movement and region re-weighting scheme were proposed based on users* feedback information. It is worth noting that the region weights that coincided with human perception can not only be used in a query session but be also memorized and accumulated for future queries. Alternatively, it is argued that the existing techniques designed around query refinement based on the RF strategy often suffer from slow convergence, and do not guarantee to find intended targets. For this, Liu et al. proposed several efficient query-point movement methods (naive random scan, local neighboring movement, neighboring divide-and-conquer and global divide-and-conquer) in reference [9]. They proved that their method was able to reach any given target image with fewer iterations in the worst and average cases. For more details and a more complete explanation of this approach, please refer to the corresponding literature.

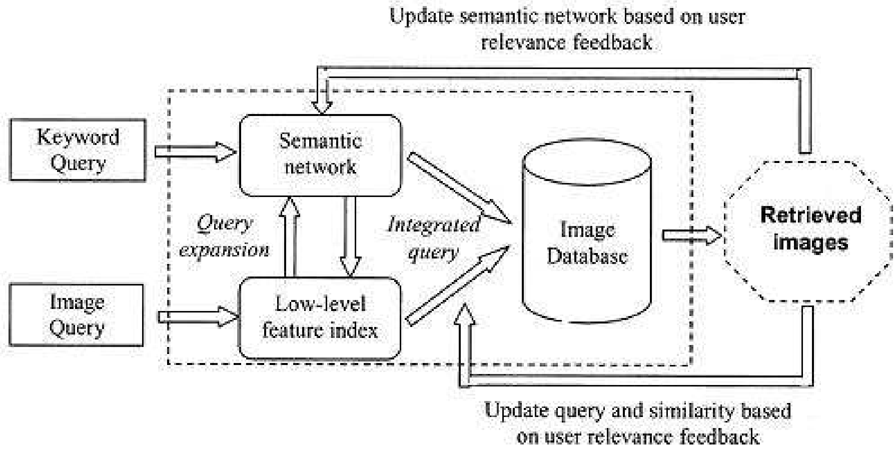

FIGURE 2. The framework of integrated RF and query expansion

3.2. **Feature re-weighting for CBIR.** The feature re-weighting method [10,11,12] was one of the most popular formulations for relevance feedback. In these approaches, each feature component was associated with a weight. Once the weights were determined by the learning methods, these weights were then employed to measure the image distance using a weighted scheme. Simply speaking, the feature re-weighting method associated larger weights with more important dimensions while smaller weights with less important ones.

Note that in the early years of the research, *tf-idf* representation was borrowed from document information retrieval in the context of image retrieval. It was possible to relate *tf-idf* to the feature weightings obtained from probabilistic models but this relation was not strong. MindrReader was an optimization approach to derive the ideal query and feature weights by combining ideas from QPM and axis re-weighting together. It was able to achieve better results by using a generalized weighted distance. In addition, some interactive retrieval approaches were also proposed which took into account the user's high-level query and perception subjectivity by dynamically updating certain weights. Particularly, the hierarchical distance model was used to define the image distance as a combination of multiple features' distances [3]. As a probabilistic feature relevance feedback method, PFRL aimed to weight each feature according to the information extracted from the relevant images. Specifically, this method applied a weighted Euclidean metric to measure the similarity between images:

$$D(I_i, I_j) = \sqrt{\sum_{k=1}^{d} w_k (f_{ik} - f_{jk})^2} \tag{2}$$

The weights related to the first retrieval were set to a common value, as no relevance information was available. After the first iteration, relevant images were used to compute the weights related to each feature according to the following formula:

$$w_k = \frac{\exp(Tr_k(Q_0))}{\sum_{n=1}^{d} \exp(Tr_n(Q_0))} \tag{3}$$

where r_k was the fraction of relevant images falling into a neighborhood of query Q_0, the neighborhood being computed on the k-th feature dimension. d denoted the dimension of the neighborhood, T was used to control the influence r_k on w_k.

In [10], irrelevant feedbacks were also included to refine the learning process. To be specific, a query was first formulated using positive example, subsequently negative example was leveraged to refine the system's response during the relevance feedback process. At the same time, Wu et al. [4] put forward a feature re-weighting approach by using relevant images as well as irrelevant ones in the relevance feedback. Due to the feature re-weighting process was prone to be trapped by suboptimal states, they introduced a disturbing factor based on the Fisher criterion to push the feature weights out of sub-optimum. On the other hand, it should be noted that the region-based approach to image retrieval has emerged as one of the most active research directions in the past few years. Jing et al. [11] presented a region weighting scheme based on the user's relevance feedback information. More recently, to make up for the drawback of the inflexible re-weighting problem of RF in image retrieval, Xu et al. [12] brought forward a re-weighting relevance feedback method based on the particle swarm optimization to optimize weightings according to user's retrieval requirement, etc.

3.3. **Bayesian method for CBIR.** As a kind of relevance feedback strategies, Bayesian method has become one of the popular research topics in the field of content-based image retrieval. In the early notable work [13], the representative image retrieval system was developed based on the Bayesian relevance feedback. Pichunter's performance, however, depended on the consistency of users' behavior and the accuracy of the prediction algorithm. Moreover, it did not guarantee to find target images and suffered from local maximum traps. In [14], a stochastic-comparison search strategy was constructed to replace the image display strategy for Pichunter, which could be incorporated into virtually any kind of existing database retrieval systems by optimizing the relevance feedback phase that by contrast can be done in a fairly universal manner, that was to say, all information about the media and users was encapsulated in a single stochastic model. Furthermore, this relevance feedback algorithm was also strong enough to be used without a query language, which was useful for domains where a query language would be awkward or new domains for which query languages had not yet been devised.

In the literatures [2,15], the Bayesian learning was exploited to incorporate user feedbacks to update the probability distribution of all the images in the database. They considered the feedback examples as a sequence of independent queries and tried to minimize the retrieval error by Bayesian rules as follows:

$$\begin{aligned} g(x) &= \arg\max_i P(y=i|x_1,\cdots,x_t) \\ &= \arg\max_i \{P(x_t|y=i)P(y=i|x_1,\cdots,x_{t-1})\} \end{aligned} \tag{4}$$

where $\{x_1,\cdots,x_t\}$ denoted a sequence of queries (feedback examples) and the probability formula $P(y=i|x_1,\cdots,x_t)$ was a prior belief about the ability of the i-th image class to explain the queries.

Compared with references [2,15], each of the positive examples was treated as a member of the same semantic class and the Bayesian classifier was employed to figure out the feature distribution of each semantic class by reference [16,17]. The work [5] could be viewed as an extended version of [16,17] by increasing the feature subspace, which was extracted and updated during the feedback process using a principal component analysis (PCA) technique. In addition, due to the involvement of image segmentation and similarity evaluation, the performance of region-based feedback of CBIR systems will be inevitably undermined. Based on this recognition, it is argued that a better formulation was to view the problem as Bayesian inference and relied on probabilistic image representations [18]. In the approach [19], a new Bayesian method for content-based image retrieval was proposed by considering CBIR as a two-class classification problem. Zhang et al. [20] developed a novel approach named BALAS to stretch Bayesian learning to solve the small sample collection and asymmetric sample distributions between positive and negative samples problems. At the same time, a CBIR system was developed based on the Bayesian relevance feedback [21].

Alternatively, it is argued that the relevance feedback techniques employed to deal with global image features only were apparently not the best choice. As it has been found that users are usually more interested in specific regions rather than the entire image, most current CBIR systems were region-based and they performed region segmentation on images so as to incorporate local information into image representation and image matching criterion [22]. On the other hand, since region-based representation is able to integrate both of local information and their spatial organization, region-based content based image retrieval is more capable of providing greater flexibility and better functionality than image-based CBIR. As a result, the region-based image retrieval (RBIR) has been widely investigated over the past several years and much endeavor has been devoted to enhancing its performance [9,23-29]. In more recent work [29], a Bayesian active learning mechanism was proposed to overcome the small sample collection and asymmetric sample distributions between positive and negative samples. Note that another proposal for using the Bayesian framework, but in a somewhat different context that includes multimedia data, is given in Ref. [30]. More details can be gleaned from the corresponding literature. To sum up, in the research of Bayesian relevance feedback in the context of CBIR, although each method has their own advantages and disadvantages, most of these can achieve satisfactory performance and motivate researchers to explore more effective image retrieval methods with the help of their excellent experiences and knowledge. Note that Table 2 lists a non-exhaustive taxonomy of RF algorithms from two aspects of short-term learning and long-term learning, respectively.

Table 2. A non-exhaustive taxonomy of relevance feedback algorithms

Short-term learning	Heuristic-based (feature axis weighting). Density estimation-based Classification-based Comparison searching-based. MDS-based interactive visualization
Long-term learning	Heuristic-based Information retrieval- and data mining-based. Incremental learning-based

4. **Other Relevance Feedback for CBIR.** Apart from the relevance feedback strategies aforementioned, there also exist some other RF methods in image retrieval community. In the early years of RF, MacArthur et al.[31] used a decision tree algorithm to sequentially cut the feature space until all the points in the feature space within a partition were of the same class. As seen from the literatures, classification techniques from the machine learning field have been extensively used in the recent literature to solve for the relevance feedback problem of image retrieval, such as the SVM active learning method [32] and the Biasmap [33], both using a kernel form to deal with the nonlinear classification boundaries, with the former exploring the active learning issue while the latter emphasizing the small sample collection issue.

In [34], genetic algorithm (GA) based relevance feedback was constructed for image retrieval by using local similarity patterns. Meanwhile, King et al.[35] presented a relevance feedback framework with integrated probability function (IPF) that combined multiple

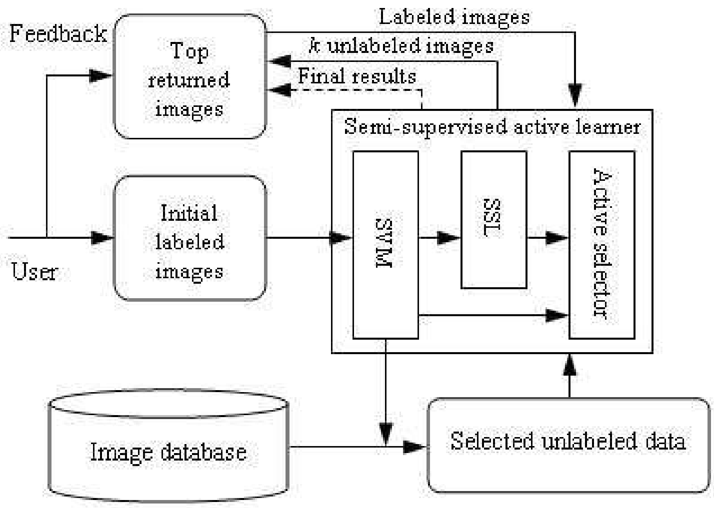

FIGURE 3. Architecture of the image retrieval framework

features for optimal image retrieval. Gosselin et al.[36] investigated active learning to RF by using binary classifiers to distinguish relevant and irrelevant classes. In addition, Hoi et al.[37] adapted the semi-supervised active learning framework to incorporate relevance feedback in image retrieval. Fig.3 displays the architecture of this image retrieval framework.

Besides, an experience-based relevance feedback search technique was presented in [38], where both CBIR and keyword-based image retrieval complement each other. As shown in [39], the one-class support vector machine was applied to solve the multiple instance learning problem in region-based image retrieval (RBIR) based on semantic regions instead of the whole image. In the meanwhile, relevance feedback technique was incorporated to provide progressive guidance to the learning process. In recent work [40], a co-training learning strategy for relevance feedback was proposed. Wang et al.[41] came up with a relevance feedback technique for CBIR based on the neural network learning by transferring the process of relevance feedback into a learning problem of neural network. After that, Len et al.[42] presented an iterative relevance feedback scheme based on logistic regression analysis for ranking a set of images in decreasing order of their evaluated relevance probabilities. In particular, this algorithm considered the probability of an image belonging to the set of those sought by the user, and modeled the logit of this probability as the output of a generalized linear model whose inputs were the low-level image features. In the scheme [43], Kim et al. proposed a relevance feedback approach based on multi-class SVM learning and cluster merging that could significantly improve the retrieval performance in region-based image retrieval (RBIR). Fig. 4 illustrates the framework of the RBIR with relevance feedback using multi-class SVM learning.

In addition, a relevance feedback approach was provided in [44] for CBIR by applying Gaussian mixture model (GMM) of the image features and a query that was updated in a probabilistic manner. Note that this update reflected the preferences of the user and was based on the models of both the positive and negative feedback images, and the retrieval was based on a recently proposed distance measure between probability density functions that could be computed in a closed form for GMM. In more recent work [45], an SVM-based relevance feedback was proposed for RBIR. In [46], two CBIR frameworks with

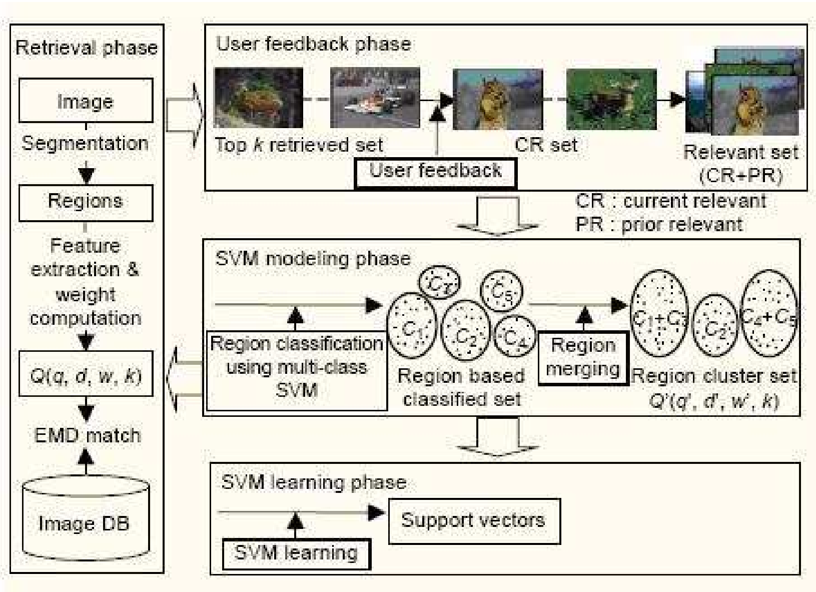

FIGURE 4. RBIR with RF using multi-class SVM learning

relevance feedback based on genetic programming (GP) were presented. Notice that the first framework exploited only the user indication of relevant images whereas the second one considered not only the relevant but also the images indicated as non-relevant. Table 3 provides some classic RF strategies mentioned in this paper, including their sources, classifiers and image datasets adopted.

5. **Conclusions and Future Work.** Relevance feedback is an important tool to improve the performance of content-based image retrieval. RF, in other words, is an interactive process to refine the retrieved results. As shown in the literature, even though much endeavor has been devoted to the development of relevance feedback approaches for content-based image retrieval, there are only very few systematic review researches on RF. So the current paper focuses our review on the relevance feedback techniques from three aspects of query-point movement, feature re-weighting and Bayesian method respectively, the ultimate goal is to complement the existing surveys in the literature each other.

However, there are still many open research issues that need to be solved before the current image retrieval system can be of practical use. First, one of the main issues associated with relevance feedback is the small sample problem. This is because users usually do not have the patience to label a large number of images. As a result, the performance of RF methods is often constrained by insufficient training samples. So how to find solutions to solve the small sample problem faced by relevance feedback is an imperative task. Second, in much of the work on RF, the images for which the user is asked to provide feedback at the next round are simply those that are currently considered by the learner as potentially the most relevant. Also, in a few cases these images are randomly selected. Thus how to understand the goals of the selection criterion in RF and how it can be improved are of great importance. Third, another common drawback of the existing relevance feedback is that they generally ignore the similarity function defined for each available descriptor. In some RF approaches, the learning process is only based on feature vectors, whilst others define specific distance functions for computing the similarity between two images. In both cases, the overall effectiveness of the CBIR

TABLE 3. A non-exhaustive taxonomy of relevance feedback algorithms

Sources	**Classifiers**	**Image Datasets**
Vasconcelos et al.[1]	Bayesian RF	BRODATZ/COLUMBIA Datasets
Wu et al.[4]	Feature re-weighting RF	COREL Dataset
Su et al.[5]	Bayesian RF, PCA	COREL Dataset
Liu et al.[9]	QPM RF	COREL Dataset
Kherfi et al.[10]	RF	OTHER Datasets
Jing et al.[11]	RF, K-means	COREL Dataset
Xu et al.[12]	RF, PSO	COREL Dataset
Su et al.[17]	Bayesian RF	COREL Dataset
Zhang et al.[20]	BALAS	COREL Dataset
Giacinto et al.[21]	Bayesian RF	COREL/MIT/UCI Datasets
Hsu et al.[24]	Bayesian RF	COREL Dataset
Duan et al.[25]	Bayesian RF	COREL Dataset
Ves et al.[26]	Bayesian RF	OTHER Datasets
Zhang et al.[27]	BALAS	COREL Dataset
Heller et al.[28]	Bayesian model	COREL Dataset
Wu et al.[29]	Bayesian RF, Active learning	COREL Dataset
Stejic et al.[34]	GA-based RF, LSP	COREL/OTHER Datasets
Zhang et al.[39]	RF, SVM, MIL	COREL Dataset
Kim et al.[43]	RF, SVM	COREL Dataset
Marakakis et al.[44]	RF, GMM	COREL/OTHER Datasets
Ferreira et al.[46]	RF, GP, GMM	COREL/FISH/MPEG7 Datasets

system may decrease if the similarity functions of the descriptors are not used. So how and when to make use of the similarity functions appropriately is a worthy research direction. Last but not the least, it is worth noting that the scaling of relevance feedback to very large-scale image datasets is also an important issue to be studied.

Acknowledgment. The author would like to sincerely thank the anonymous reviewers for their valuable comments and insightful suggestions that have helped to improve the paper. Also, the author thanks Professor Zhongzhi Shi for stimulating discussions and helpful hints. This work is partially supported by the National Program on Key Basic Research Project (No.2013CB329502), the National Natural Science Foundation of China (No.61202212) and the Key Research Project of Baoji University of Arts and Sciences (No.ZK18012).

REFERENCES

[1] T. Huang and X. Zhou, Image retrieval with relevance feedback: from heuristic weight adjustment to optimal learning methods, *Proc. of the 8th Int'l Conf. on Image Processing (ICIP'01)*, pp. 2–5, 2001.

[2] I. Cox, M. Miller, T. Minka, et al., The Bayesian image retrieval system, PicHunter: theory, implementation and psychophysical experiments, *IEEE Transactions on Image Processing*, vol. 9, no. 1, pp. 20–37, 2000.

[3] Y. Rui and T. Huang, Optimizing learning in image retrieval, *Proc. of the Int'l Conf. on Computer Vision and Pattern Recognition (CVPR'00)*, pp. 1236–1243, 2000.

[4] Y. Wu and A. Zhang, A feature re-weighting approach for relevance feedback in image retrieval, *Proc. of the 9th Int'l Conf. on Image Processing (ICIP'02)*, pp. 581–584, 2002.

[5] Z. Su, H. Zhang, S. Li, et al., Relevance feedback in content-based image retrieval: Bayesian framework, feature subspaces, and progressive learning, *IEEE Transactions on Image Processing*, vol. 12, no. 8, pp. 924–937, 2003.

[6] H. Wu, H. Lu and S. Ma, The role of sample distribution in relevance feedback for content-based image retrieval, *Proc. of the Int'l Conf. on Multimedia and Expo (ICME'02)*, pp. 225–228, 2002.

[7] Y. Lu, H. Zhang, W. Liu, et al., Joint semantics and feature based image retrieval using relevance feedback, *IEEE Transactions on Multimedia*, vol. 5, no. 3, pp. 339–347, 2003.

[8] F. Jing, M. Li, H. Zhang, et al., Relevance feedback in region-based image retrieval, *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 14, no. 5, pp. 672–681, 2004.

[9] D. Liu, K. Hua, K. Vu, et al., Fast query point movement techniques for large cbir systems, *IEEE Transactions on Knowledge and Data Engineering*, vol. 21, no. 5, pp. 729–743, 2009.

[10] M. Kherfi, D. Ziou and A. Bernardi, Learning from negative example in relevance feedback for content-based image retrieval, *Proc. of the Int'l Conf. on Pattern Recognition (ICPR'02)*, pp. 933–936, 2002.

[11] F. Jing, M. Li, H. Zhang, et al., Learning region weighting from relevance feedback in image retrieval, *Proc. of the Int'l Conf. on Acoustics, Speech, and Signal Processing (ICASSP'02)*, pp. 4088–4091, 2002.

[12] X. Xu, X. Liu, Z. Yu, et al., Re-weighting relevance feedback image retrieval algorithm based on particle swarm optimization, *Proc. of the 6th Int'l Conf. on Natural Computation (ICNC'10)*, pp. 3609–3613, 2010.

[13] I. Cox, M. Miller, S. Omohundro, et al., PicHunter: Bayesian relevance feedback for image retrieval, *Proc. of the Int'l Conf. on Pattern Recognition (ICPR'96)*, pp. 361–369, 1996.

[14] I. Cox, M. Miller, T. Minka, et al., An optimized interaction strategy for Bayesian relevance feedback, *Proc. of the Int'l Conf. on Computer Vision and Pattern Recognition (CVPR'98)*, 1998.

[15] N. Vasconcelos and A. Lippman, Bayesian representations and learning mechanisms for content based image retrieval, *Proc. of the SPIE Conf. on Storage and Retrieval for Media Databases (SRMD'00)*, pp. 43–54, 2000.

[16] Z. Su, H. Zhang and S. Ma, An image retrieval relevance feedback algorithm based on the Bayesian classifier, *Journal of Software*, vol. 13, no. 10, pp. 2001–2006, 2002.

[17] Z. Su, H. Zhang and S. Ma, Using Bayesian classifier in relevant feedback of image retrieval, *Proc. of the 12th Int'l Conf. on Tools with Artificial Intelligence (ICTAI'00)*, pp. 258–261, 2000.

[18] N. Vasconcelos and A. Lippman, Bayesian relevance feedback for content-based image retrieval, *Proc. of the IEEE Workshop on Content-based Access of Image and Video Libraries*, pp. 63–67, 2000.

[19] J. Tao and Y. Hung, A Bayesian method for content-based image retrieval by use of relevance feedback, *Recent Advances in Visual Information Systems, LNCS 2314*, pp. 76–87, 2002.

[20] R. Zhang and Z. Zhang, Stretching Bayesian learning in the relevance feedback of image retrieval, *Proc. of the 8th European Conf. on Computer Vision (ECCV'04)*, pp. 355–367, 2004.

[21] G. Giacinto and F. Roli, Bayesian relevance feedback for content-based image retrieval, *Pattern Recognition*, vol. 37, no. 7, pp. 1499–1508, 2004.

[22] F. Jing, M. Li, H. Zhang, et al., An efficient and effective region-based image retrieval framework, *IEEE Transactions on Image Processing*, vol. 13, no. 5, pp. 699–709, 2004.

[23] R. Zhang, J. Yuan, J. Huang, et al., A novel generalized SVM algorithm with application to region-based image retrieval, *Proc. of the Int'l Forum on Information Technology and Applications (IFITA'09)*, pp. 280–283, 2009.

[24] C. Hsu and C. Li, Relevance feedback using generalized Bayesian framework with region-based optimization learning, *IEEE Transactions on Image Processing*, vol. 14, no. 10, pp. 1617–1631, 2005.

[25] L. Duan, W. Gao, W. Zeng, et al., Adaptive relevance feedback based on Bayesian inference for image retrieval, *Signal Processing*, vol. 85, no. 2, pp. 395–399, 2005.

[26] E. Ves, J. Domingo, G. Ayala, et al., A novel Bayesian framework for relevance feedback in image content-based retrieval systems, *Pattern Recognition*, vol. 39, no. 9, pp. 1622–1632, 2006.

[27] R. Zhang and Z. Zhang, BALAS: Empirical Bayesian learning in the relevance feedback for image retrieval, *Image and Vision Computing*, vol. 24, no. 3, pp. 211–223, 2006.

[28] K. Heller and Z. Ghahramani, A simple Bayesian framework for content-based image retrieval, *Proc. of the Int'l Conf. on Computer Vision and Pattern Recognition (CVPR'06)*, pp. 2110–2117, 2006.

[29] J. Wu, Y. Fu and M. Lu, Bayesian active learning in relevance feedback for image retrieval, *Proc. of the 2nd Int'l Symp. on Intelligent Information Technology Application (IITA'08)*, pp. 371–375, 2008.

[30] N. Freitas, E. Brochu, K. Barnard, et al., Bayesian models for massive multimedia databases: a new frontier, *Technical Report TR-2003-5*, Department of Computer Science, University of British Columbia.

[31] S. MacArthur, C. Brodley and C. Shyu, Relevance feedback decision trees in content-based image retrieval, *Proc. of the IEEE Workshop on Content-Based Access of Image and Video Libraries (CBAIVL'00)*, pp. 68–72, 2000.

[32] S. Tong and E. Chang, Support vector machine active learning for image retrieval, *Proc. of the 9th Int'l Conf. on Multimedia (MM'01)*, pp. 107–118, 2001.

[33] X. Zhou and T. Huang, Small sample learning during multimedia retrieval using biasmap, *Proc. of the Int'l Conf. on Computer Vision and Pattern Recognition (CVPR'01)*, 2001.

[34] Z. Stejic, Y. Takama and K. Hirota, Genetic algorithm-based relevance feedback for image retrieval using local similarity patterns, *Information Processing & Management*, vol. 39, no. 1, pp. 1–23, 2003.

[35] I. King and Z. Jin, Integrated probability function and its application to content-based image retrieval by relevance feedback, *Pattern Recognition*, vol. 36, no. 9, pp. 2177–2186, 2003.

[36] P. Gosselin and M. Cord, A comparison of active classification methods for content-based image retrieval, *Proc. of the 1st Int'l Workshop on Computer Vision Meets Databases (CVDB'04)*, pp. 51–58, 2004.

[37] S. Hoi and M. Lyu, A semi-supervised active learning framework for image retrieval, *Proc. of the Int'l Conf. on Computer Vision and Pattern Recognition (CVPR'05)*, pp. 302–309, 2005.

[38] C. Ng and G. Martin, Experience-based relevance feedback for image retrieval, *Proc. of the 2nd European Workshop on the Integration of Knowledge, Semantics and Digital Media Technology (EWIMT'05)*, pp. 245–252, 2005.

[39] C. Zhang, X. Chen, M. Chen, et al., A multiple instance learning approach for content based image retrieval using one-class support vector machine, *Proc. of the Int'l Conf. on Multimedia and Expo (ICME'05)*, pp. 1142–1145, 2005.

[40] Z. Zhou, K. Chen and H. Dai, Enhancing relevance feedback in image retrieval using unlabeled data, *ACM Transactions on Information Systems*, vol. 24, no. 2, pp. 219–244, 2006.

[41] B. Wang, X. Zhang and N. Li, Relevance feedback technique for content-based image retrieval using neural network Learning, *Proc. of the 5th Int'l Conf. on Machine Learning and Cybernetics (ICMLC'06)*, pp. 3692–3696, 2006.

[42] T. Leon, P. Zuccarello, G. Ayala, et al., Applying logistic regression to relevance feedback in image retrieval systems, *Pattern Recognition*, vol. 40, no. 10, pp. 2621–2632, 2007.

[43] D. Kim, J. Song, J. Lee, et al., Support vector machine learning for region-based image retrieval with relevance feedback, *ETRI Journal*, vol. 29, no. 5, pp. 700–702, 2007.

[44] A. Marakakis, N. Galatsanos, A. Likas, et al., Probabilistic relevance feedback approach for content-based image retrieval based on Gaussian mixture models, *IET Image Processing*, vol. 3, no. 1, pp. 10–25, 2009.

[45] Z. Zeng, S. Cai and S. Liu, A novel image representation and learning method using SVM for region-based image retrieval, *Proc. of the 5th Int'l Conf. on Industrial Electronics and Applications (ICIEA'10)*, pp. 1622–1626, 2010.

[46] C. Ferreira, J. Santos, R. Torres, et al., Relevance feedback based on genetic programming for image retrieval, *Pattern Recognition Letters*, vol. 32, no. 1, pp. 27–37, 2011.