# CHAPTER 5

# UNCERTAINTY BASED SAMPLING APPROACH FOR RELEVANCE FEEDBACK

CBIR system sometimes fails to precisely retrieve desired images. Then it is useful to refine the results using the feedback given by the user for the retrieved results in multiple iterations. Relevance feedback is a process in which user feedback is important. An image retrieval system presents a ranked set of images which are relevant to the user's initial query and then iteratively solicits the user for feedback on the relevance of images and uses the feedback to compose and improve the retrieval result.

Human interactive systems have attracted a lot of research interest in recent years, especially for CBIR systems. Several interactions between the user and the system have been proposed [104], usually; user information consists of binary labels specifying whether the image belongs to the desired concept or not. The positive labels indicate relevant images for the desired concept, and the negative labels indicate irrelevant images. The relevance feedback is based on the strategy of query concept updating. The aim of this strategy is to refine the query according to the user labeling [105]. There are mainly two approaches for query concept updating strategy, an approach, called query modification, forms a new query by averaging the feature vectors of relevant images [103]. Another approach, the query reweighting, computes a new similarity function between the query and the images in database to refine the result.

Active learning is a technique that uses uncertainty based sampling approach for relevance feedback. An image in the pool of unlabeled images is ranked by the learner. The relevance function of a learner program has to classify the images as relevant or irrelevant. Some images are certainly relevant, others are irrelevant, but some may be more difficult to classify. Uncertainty-based sampling strategy aims at selecting unlabeled images that the learner is most uncertain about.

In this chapter, we present an active learning approach based on uncertainty based sampling for relevance feedback to iteratively refine the results, retrieved by CBIR system.

## 5.1 Relevance Feedback Based Search Paradigm

The system which improves its own performance based on the experience is considered as the machine-learning system [113]. In CBIR, relevance feedback improves the retrieval performance based on the feedback examples provided by the users. Hence, classical machine-learning methods, such as decision tree learning [119], artificial neural networks [118], Bayesian learning [123], and kernel based learning [122] are usually used for relevance feedback.

Users are generally reluctant to provide a large number of feedback examples; thus the number of training samples is very small, typically less than ten in each round of the feedback session. On the contrary, feature dimensions in CBIR systems are usually very high. Hence, the crucial issue in improving performance of relevance feedback in CBIR systems is how to learn from small training samples in a very high dimension feature space. This fact makes many learning methods, such as decision tree learning and artificial neural networks, not suitable for CBIR [120].

Some researchers consider a relevance feedback process in CBIR as a pattern recognition or classification problem. Under such a consideration, the positive and negative examples provided by user can be treated as training examples and a classifier is trained based on those examples. Then, such classifier separates all data set into relevant and irrelevant groups. Many existing pattern recognition tools and classifiers have been experimented by various researchers, such as a linear classifier [125], nearest-neighbor classifier [124], Bayesian classifier [120], support vector machines (SVM) [121], and so on. The most popular algorithm is presented in [122] in the year 2011, where the SVM classifier is trained to divide the positive and negative examples. Then such SVM classifier will classify all images in database into two groups: relevant and irrelevant groups to a given query.

Active learning is a newly emerged paradigm in relevance feedback for CBIR. In the SVM-Active approach, which was developed by Tong and Chang [114], in each iteration of relevance feedback, a support vector machine is trained on labeled data and then the user is asked to label the images that are near to the support vector boundary.

## 5.2 Active Learning for Relevance Feedback

In the classification framework for CBIR, retrieving images is modeled as a two-class problem: the relevant class, the set of images similar to query concept, and the irrelevant class, composed of remaining images in a database. Active learning is based on such a classification framework of relevance feedback.

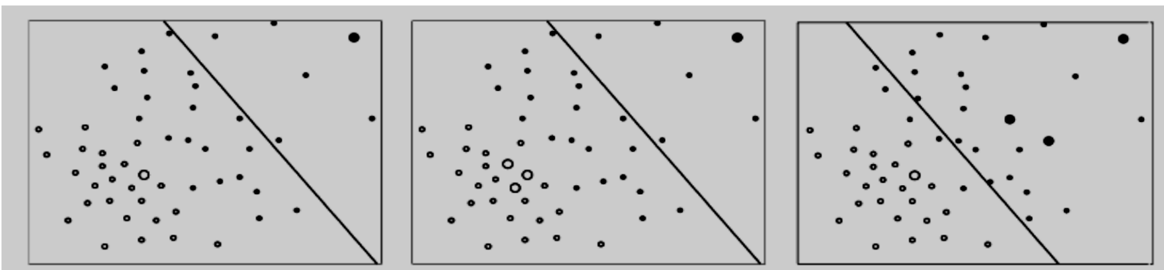
In relevance feedback, the user has to label the images as either relevant or irrelevant. The labeled images are then provided to the CBIR system as a new query so that more relevant images could be retrieved from the database. In fact, the CBIR system is considered as a machine learning process, which trains a learner to classify the images in the database into two classes. Since the classification is usually carried out with different confidence, the learner generates a rank of the images according to how relevant they are to the user query. The higher the rank, the more relevant the corresponding image. After receiving the user feedback, the machine learning process uses the newly labeled images along with the original user query to retrain the learner, so that a new rank could be produced which typically puts more relevant images at higher ranks than the original one did. This is a supervised learning approach, where only labeled data are used in the training of the learner. In CBIR, since it is not convenient to ask the user to label many images, the labeled training examples given by the user query and relevance feedback are very small, and pure supervised learning from such a small training set is hard to obtain good generalization performance.

To deal with the problem of training the learner with a very less number of examples in a high dimensional feature space, active learning uses two alternative approaches, uncertainty based sampling and committee based sampling. The uncertainty based sampling approach train a learner based on the uncertainty of users label. The committee-based sampling [126] generate a committee of several learners and choses the unlabeled instances on which the committee members disagree.

Uncertainty-based sampling strategy usually uses two different approaches, a first approach proposed by Cohn [108] uses several classifiers with the same training set, and selects samples whose classifications are the most contradictory. Another solution is to compute a probabilistic output for each sample, and selecting the unlabeled samples with the probabilities closest to 0.5 [108]. Similar strategies have also been proposed with SVM classifier [112], with a theoretical justification [124], and with nearest neighbor classifier [103].

### 5.2.1 Example of Uncertainty Based Sampling Strategies

In this example, the images are represented by 2-D feature vectors, the white circles are images the user is looking for, and the black circles are the images the user is not interested in. At the beginning, the user provided two labels; represented in figures by larger circles. These two labels allow the system to compute a first classification. In classical relevance feedback systems, a common way of selection was to label the most relevant pictures returned by the system. As shown in Fig. 2 (b), this choice is not effective, since in that case the classification is not improved. The other way to select the label is to use the active learning with uncertainty based sampling. In this the user labels the images which are very close to the classification boundary. As shown in Fig. 2(c).



**(a)** **(b)** **(c)**

**Fig.5.1 Active Learning Example**

## 5.3 Proposed Active learning Strategy for Relevance Feedback

In CBIR, the user initiates the retrieval process by providing a query image to the system. From the view of machine learning, such a user query is considered as a positive example, while the image database is a collection of unlabeled images. Let $U$ denote the unlabeled data set of images while $L$ denote the labeled data set, $L = P \cup N$ where $P$ and $N$ denote the sets of labeled positive examples and negative examples respectively. Initially U is the complete database DB, P is {query}, and N is empty. Let |X | denote the size of a set X. Then the size of U, P and N are |DB|, 1, and 0, respectively.

In relevance feedback, the user may label several images according to whether they are relevant to the query image or not, which is considered as providing additional positive or negative examples. Let $P^*$ and $N^*$ denote the new positive and negative examples, respectively. Since the feedback is usually performed on images in the database, both $P^*$ and $N^*$ are subsets of DB. Therefore, the relevance feedback process updates $L$ and $U$. For $L$, its positive subset $P$ is enlarged to be $P \cup P^*$, and its negative subset $N$ is enlarged to be $N \cup N^*$; but for $I$, since some of its elements have been moved to $L$, it is shrunk to be $U - (P^* \cup N^*)$.

After obtaining the enlarged $P$ and $N$, in each iteration of relevance feedback, a traditional CBIR system would retrain learners, which then give every image in $U$, a rank expressing how relevant the image is to the query image. It is obvious that such a rank could be more accurate than the one produced by the learner trained with only the original $P$ and $N$ because now the learner is provided with more labeled training examples. Since it is not convenient to ask the user to label many images in the relevance feedback process, in most cases the enlarged training set is still very small.

After obtaining P and N, learners are retrained and then every image in $U$ is given a rank. Here the rank is assumed to be a value between −1 and +1, where positive/negative means the learner judges the concerned image to be relevant/irrelevant, and the bigger the absolute value of the rank, the stronger the confidence of the learner.

In traditional CBIR systems, the feedback pool of images (pool for the user to give feedback) is not distinguished from the retrieved images. That is, the system gives the retrieval result, and then the user selects some images from the result to label. It is observed that in this approach, the images labeled by the user in the relevance feedback process may not be the images that are most helpful to improve the retrieval performance. Labeling an image that has already been well learned may be not very useful. Thus, uncertainty based sampling approach is used that selects the images, for which the learner of the relevance function is most uncertain.

Proposed approach does not passively wait for the user to choose images to label. Instead, it actively prepares a pool of images for the user to provide feedback. An algorithm for proposed active learning based relevance feedback for CBIR is given in Fig. 5.2

Active (query, DB,L,Pool_size,result_size)

Input: Query: User query

DB: Image database

L: learner

Pool_size: Number of images in feedback pool

Result_size: Number of images to be retrieved

P←{query}; N ←ϕ; U ←DB

**Repeat until** user is satisfied

**If** user want to give feedback

**Then**

*getfeedback* ( P*, N* )

P← P U P*; N ← N U N*; U ← U - ( P* U N* )

$P_i$←P U (arg max L (x,P,N)

$N_i$← P U (arg min L (x,P,N)

**else** **do** $P_i$←P;$N_i$←N

**for** x∈ U **do** Rank(x) $1/Z_{norm} \cdot L(x_i,P_i,N_i)$

Pool ← ϕ ; result ← ϕ

**for** I ∈{1…pool_size} **do** pool ← pool U {arg | 0.6 < rank(x) > 0.4 }

**for** I ∈{1…result_size} **do** pool ← pool U {arg max rank(x) }

**end of repeat**

**return** Result;

**Fig. 5.2 Algorithm for Proposed Active Learning Based Relevance Feedback**

In relevance feedback, the number of example images provided by the user is still very limited. However, there are large number images existing in the database which are relevant to the user query. Those images are useful for relevance feedback. It is well known fact that a main difficulty in the design of an efficient CBIR is the gap between high-level semantics and low-level image features. This problem can hardly be solved by simply using stronger visual features, but can be tackled to some degree by using more example images. In fact, the relevance feedback mechanism improves the result, simply because more example images are given by the user during the feedback process. Thus, considering the example images as labeled training examples and the images in the database as unlabeled training examples, the CBIR problem resembles what has motivated the research on learning with unlabeled examples. That is, there are limited number of labeled training examples which are not sufficient for training a strong learner, but there are abundant unlabeled training examples which can be exploited. So, it is evident that techniques of learning with unlabeled data can be used to help improve the retrieval performance.

The volume of data that can be manually annotated is limited due to the cost of manual intervention. Deciding which samples will be more useful in the relevance feedback iteration, is the crucial factor to improve the retrieval result. Active learning is an approach in which an existing system is used to predict the usefulness of new samples. This approach is a particular case of incremental learning in which a system is trained several times with a growing set of samples. Several strategies are considered to predict the samples usefulness. The most popular ones include:

• When several systems are available, choose the samples which maximize the disagreement amongst them ("query by committee" [114]). This strategy cannot be used if a single system is available.

• Choose the most uncertain samples. This strategy tries to increase the sample density in the neighborhood of the frontier between positives and negatives and therefore improve the system's precision.

• Choose the most probable positive samples. This strategy tries to maximize the size of the set of positive.

More complex strategies can be used, including combinations of these. For instance, the system may choose the samples for annotation amongst the most probable ones and amongst the farthest from the already evaluated ones. Another possibility is to select samples by groups in which maximize the expected global knowledge gain [111].

## 5.4Experimental Results

We have evaluated the retrieval performance of the proposed feature extraction methods, FC and VC by using the database which consists of images solely of landscape scenes. There are 1000 images in our database collected from image album published by

Corel Corp. These 1000 images comprise of six image classes, each of which contains 200 images. In other words, each image has a known class identity. These six classes are views of (a) Mountains, (b) Sunset, (c) Sea, (d) Lands & Skies (e) Flowers.

Fig.5.6 (a) shows the retrieval results for a query image *'mountain'*. The retrieved images are arranged in descending order of similarity with the query image, shown in Fig. 5.6 (b). Uncertain class of images is then selected using the proposed strategy and presented separately as a pool of feedback images, which is shown in Fig. 5.6 (c).

The refined results after the relevance feedback is shown in Fig. 5.6 (c). It is observed that the results after the iteration of relevance feedback are more relevant to the image query.

Query image

**(a)**

**Retrieved Results**

**(b)**

**Pool for feedback**

**(c)**

**New Query (from the feedback pool )**

**(d)**

**Retrieved results**

**(e)**

**Fig. 5.3 Retrieval Results of Proposed Active Learning Based Relevance Feedback**

The retrieval performance of our proposed uncertainty based active learning approach is measured in terms of evaluation measures such as F-measure, NDCG and average retrieval precision [21], which are discussed in chapter 3. Each time a query image is selected from the database to retrieve 25 best matched images, excluding the query image itself, from the database. Table 5.1 summarized the performance of the proposed approach.

| Parameter/Query Concept | Red Rose | Sea | farms | Mountains& Rivers | Land & Skies |
|---|---|---|---|---|---|
| **Precision** | 0.44 | 0.48 | 0.48 | 0.40 | 0.52 |
| **Recall** | 0.69 | 0.75 | 0.75 | 0.63 | 0.81 |
| **F measure** | 0.54 | 0.59 | 0.59 | 0.49 | 0.63 |
| **FB** | 0.47 | 0.52 | 0.52 | 0.43 | 0.56 |
| **Average Precision** | 0.54 | 0.61 | 0.63 | 0.55 | 0.68 |
| **NDCG** | 0.86 | 0.91 | 0.92 | 0.82 | 0.92 |

**Table 5.1 Retrieval Performance of the Proposed Uncertainty Based Active Learning Approach**.

To compare the performance of our proposed approach with the conventional relevance feedback, three strategies have been evaluated. The first strategy is to always select the most probable positive samples. The second strategy is to always select the most uncertain samples. The third strategy in rather an absence of strategy and corresponds to a random choice, it is used as a baseline for the other two. The system always outputs a score for each test sample. In the “most probable” strategy, samples with the probability closer to 1.0 are selected. In the “most uncertain” strategy, samples with the probability closer to 0.5 are selected. It is observed from the experimental results that the proposed uncertainty based sampling approach outperform the other sampling strategies. The precision recall curve shows the significant enhancement in retrieval performanace  with the proposed approach.

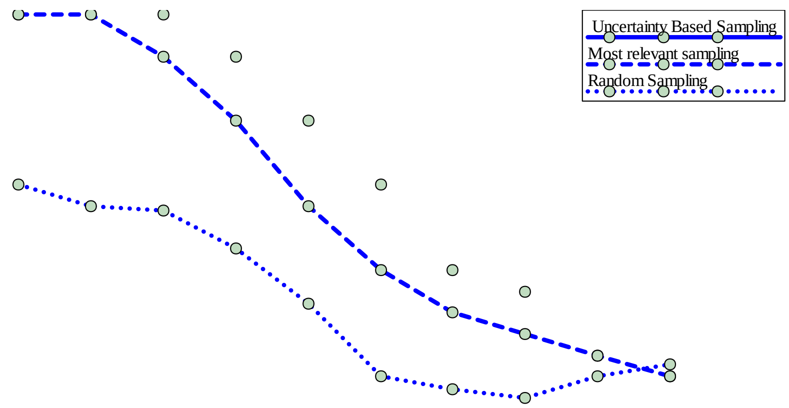



**Fig. 5.6 Retrieval performance of three strategies: uncertainty based sampling, most relevant sampling and random sampling**

## 5.5Conclusion

In this chapter, a novel learning approach for relevance feedback is proposed, which is based on the principal of uncertainty based sampling. The proposed approach exploits unlabeled data to improve the performance of content-based image retrieval (CBIR).In each iteration of relevance feedback, a learner is trained from the labeled data, i.e. images from user query and user feedback. A learner classifies the unlabeled images in the database into either relevant class or irrelevant class. Uncertainty-based sampling strategy aims at selecting unlabeled samples that the learner is the most uncertain about. Most relevant images are displayed as the retrieval result, while the uncertain samples are put into the pool which is used in the next iteration of relevance feedback. Experimentally it is observed that the proposed active learning method enhances the retrieval performance in successive iteration of relevance feedback.