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# Automatic Relevance Feedback for Distributed Content-Based Image Retrieval

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## Abstract

In this paper, we present the machine-controlled relevance feedback technique for the distributed content-based image retrieval (CBIR) system. A nonlinear model based on the Gaussian-shaped radial basis function (RBF) is applied in the feedback process, and a bias weighting is introduced to the query content as the partial supervised function to improve the retrieval precision. This paper introduces a decentralized Peer-to-Peer CBIR algorithm which reinforces offline feature calculation technique to generate a distributed feature descriptor database (DFDD), to offload feature computation to the P2P network while improving the retrieval precisions. In addition, this paper compares the retrieval performance over centralized, clustered, and decentralized peer-to-peer network topologies. Combination of the ARF technique and the distributed CBIR system eliminates the human intervention, hence automates distributed CBIR in a hierarchical manner.

***Keywords:*** *Content Based Image Retrieval, Distributed Database, Fuzzy Algorithms, Self Organizing Tree Map.*

## 1. Introduction

Content based image retrieval (CBIR) has become one of the most promising research fields in multimedia database management. Due to the immature artificial intelligence bridging the semantic meanings and the low-level descriptors, it is a challenge to retrieve images from a large database efficiently and effectively. Finding a set of feature descriptors which best classify the multimedia content has therefore become an active research area in recent years.

Today, most content-based retrieval (CBR) systems are based on evaluating the low-level features embedded in the multimedia content. Low level features, such as color, texture, and shape, are commonly used by the CBIR systems to measure the similarities between the query and target images. To ensure the interoperability between different CBIR databases, it is important to standardize the feature descriptors. The MPEG-7 standard pulls together the recent research work in feature extraction to standardize a multimedia content description interface, thus ensures the interoperability between different CBIR systems [1]-[3].

In the internet era, rich multimedia information is easily accessible by everyone attaching to the network. While the amount of multimedia content keeps growing, locating and obtaining the desired information has become a difficult task. A typical solution for the networked CBIR system is to establish a centralized database, which maintains a hash table of the feature descriptors and the link to the content on the network, like a typical search engine on today's internet. Unfortunately, such approach demands extensive computational and network resources, and is highly inefficient for multimedia contents. An ideal networked CBIR system should aim to maximize the retrieval precision while optimizing the computational and network resources.

### *A. CBIR with relevance feedback*

A major task in the CBIR systems is the similarity matching between the query image and the retrieved images. Unfortunately, the gap between high-level concepts and low-level features, as well as the subjective perception for the visual content by the human beings, result a significant mismatch between the retrieval results judged manually and by the computers. To improve the retrieval precision, human interactions are usually involved. Relevance feedback is an interactive process which integrates users' evaluation of the retrieval results [4]-[6]. Typically, the relevance feedback technique includes an interactive scoring system to evaluate the past retrieval results to improve the subsequent content retrieval. Various techniques, such as Radial Basis Function Network (RBFN) [7], a combination of the positive and the negative feedback [8], Support Vector Machine (SVM) [9][10], and Self-Organizing Map (SOM) [11] have been investigated to improve the precision of the feedback. However, the extensive human interaction is the major drawback for a typical relevance feedback approach. To address this problem, a machine-controlled Automated Relevance Feedback (ARF) approach is proposed in [12][13]. By adopting the machine intelligence for evaluating the retrieval result, the dependence of the human interaction can be reduced by introducing a fully-automated or semi-automated CBIR system. In this paper, we propose several techniques to improve interactive and automated relevance feedback. Also, we study how ARF can help reducing the bandwidth requirement and the subjective errors caused by human feedback in the distributed CBIR scenario.

### *B. Distributed CBIR*

The growing popularity of the internet has spawned wave after wave of technical innovations. Internet tools have made digital image swapping easier than ever. Most CBIR systems assume a centralized query server, such as QBIC [14] and VisualSEEk [15]. Content query over distributed peer-to-peer (P2P) network is studied in [16][17], and Firework Query Model and DISCOVER algorithm are proposed. The Firework Query Model and DISCOVER algorithm assumes that each peer node is consist of images under the same category, which may be impractical for the image database distribution over today's Peer-to-Peer network, and hence this paper extends the scope by assuming a peer may contain more than one image category. To handle the search across a substantial amount of distributed databases, a meta-search engine (MSE) incorporating the search-agent processing model (SAPM) is proposed [18]. In this paper, we study practical scenarios where multiple image categories exist in each individual database in the distributed storage network.

### *C. Contributions*

Detailed evaluations and comparisons of the relevance feedback approach and the ARF approach for CBIR are addressed in [12][13]. This paper extends the earlier research work, by introducing the semi-supervision to the relevance feedback algorithm and demonstrates the improved retrieval precision. Comparisons betweens the monothetic clustering approach using the Fuzzy C-Means (FCM) algorithms and the polythetic clustering approach using the Self Organizing Tree Map (SOTM) are also investigated in this paper. In addition, we introduce a rank weighting to the SOTM algorithm and analyze its impact on the retrieval performance.

For load balancing the computational and the network resources of centralized CBIR database, a clustered CBIR system which pre-clusters the feature descriptors database using k-means algorithm is proposed in this paper. Distributed CBIR system over the peer-to-peer (P2P) network is introduced, which is in essence decentralizing the feature descriptor database (FDD). With the proposed technique to compute the distributed FDD (DFDD), better utilized network resources and improved retrieval precision can be achieved. An innovative incremental searching technique for distributed CBIR with ARF is also proposed in this paper. In addition, we evaluate the semi and the fully automated relevance feedback techniques based on the proposed distributed CBIR system.

The rest of the paper is organized as follows: Section (2) introduces the CBIR system with automated relevance feedback. Section (3) describes CBIR system with different network topologies. Section (4) shows the experimental result of the proposed system. Concluding remarks are given in Section (5).

## 2. Content Based Image Retrieval System

A CBIR system consists of two stages, the *feature calculation* stage and the *query* stage. In the feature calculation stage, each image's feature descriptors are extracted and stored in the database, which could be centralized (stored in a database server) or decentralized (distributed over the network). Due to the exhaustive computational requirement, the feature calculation is typically performed off-line. In the query stage, the feature descriptors of the query image are extracted on the fly, and a similarity match is performed on the server. For distributed CBIR, the query will propagate through multiple peers according to certain query order. An overview of the CBIR system is shown in Figure 1.

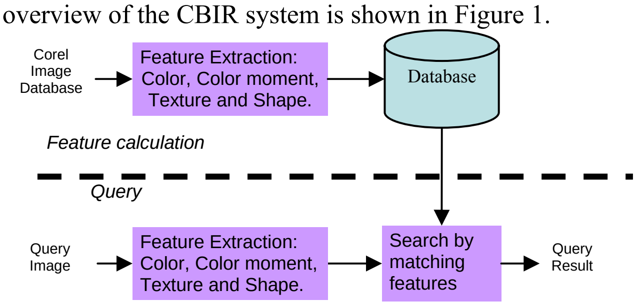



Figure 1: Content-based image retrieval systems.

### *A. Pre-Processing*

Each image in the CBIR database is pre-processed to extract the feature descriptors for similarity matching. In this paper, four feature descriptors are used: color histogram, color moment, texture, and shape feature descriptors.

<u>*Color Histogram*</u>

One of the most popular features used in CBIR is the color histogram in the HSV color space, as used in MPEG-7 descriptor [18][19]. The images are firstly converted to the HSV color space, and a 64-bin color histogram is generated by uniformly quantizing H, S, and V components into 16, 2, and 2 regions, respectively.

<u>*Color Moments*</u>

The mean $\mu$, standard deviation $\sigma$, and skew g are extracted from the R, G, and B color spaces to form a 9-dimensional feature vector [20].

<u>*Texture*</u>

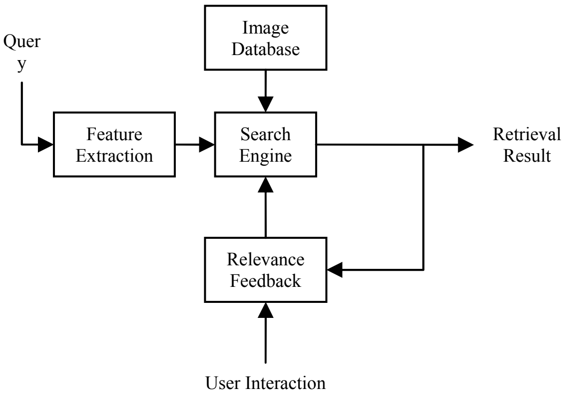
The images are first resized to 128x128 gray scale pictures, and Gabor wavelet filters are applied to generate a 48-dimension feature vector [20][21].

Sub-band based still-image compression technique has shown a better compression ratio compares to conventional block-based approach, and the JPEG-2000 standard [22] applies Daubechies wavelet filter. Simplified texture features are extracted from Daubechies wavelet subbands to reduce the computational cost since a partial decoding is only required for JPEG-2000 images.

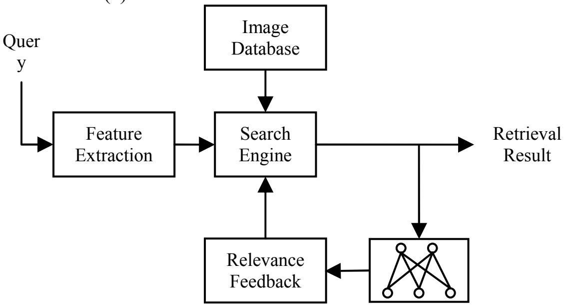
*Shape*

Sobel filter was studied in the earlier work [20] for object edge detection due to its low computational cost. In this paper, all proposed centralized and decentralized CBIR system reinforces offline feature extraction, and performance impact for the feature extraction is insignificant, Canny filter is chosen for feature extraction in this paper.

The shape parameter extracted using the Canny filter is then converted from the Cartesian coordinate to the polar coordinate system. Fast Fourier Transform (FFT) is then applied, and a 10-dimensional feature vector $s_i$ is extracted from the low frequency components.




(a) Human controlled relevance feedback




(b) Machine controlled relevance feedback
Figure 2: CBIR system with relevance feedback.

*B. Relevance Feedback with Radial Basis Function with Bias on the Query Image*

The relevance feedback process involves user interaction to identify two sets of images: the positive sample set (relevant images), $X^{+} = \{x_1, \ldots, x_m\} \subset \Re^{p}$, and the negative sample set (irrelevant images), $X^{-} = \{x'_1, \ldots, x'_n\} \subset \Re^{p}$. The positive and negative sample sets are fed back to the similarity matching engine, to improve the retrieval result in the subsequent iteration. Figure 2(a) illustrates the system diagram of CBIR with relevance feedback.

A non-linear relevance feedback approach using Gaussian-shaped radial-basis function network (RBFN) is selected [7]. The architecture of RBFN is illustrated in Figure 3. The Gaussian-shaped RBFN at $c_i$ is defined as:

$$G(x_i, c_i) = \exp\left(-\frac{\|x_i - c_i\|^2}{2\sigma_i^2}\right) \tag{1}$$

The estimation function, $f$, is the measure of the similarity of the sample dataset, which is defined as:

$$f(x, c) = \sum_{i=1}^{P} G(x_i, c_i) = \sum_{i=1}^{P} e^{-\|x_i - c_i\|^2 / 2\sigma_i^2} \tag{2}$$

The centroid, $c(t)$, is updated at each iteration:

$$c(t+1) = \overline{X}^{+} + \alpha_N \left(c(t) - \overline{X}^{-}\right) \tag{3}$$

The smoothing parameter, $\sigma_i$, is given by:

$$\sigma_i = e^{-\beta \cdot STD\left(X^{+}\right)} \tag{4}$$

where $\alpha_N$ denotes the negative weighting, $\beta$ denotes the overlapping factor, and STD is the standard deviation function.

For any incorrect decision made by ARF, the error will propagate into subsequent centroid update. To minimize the error propagation, we introduced the bias weighting $\gamma$ to the original query image, or the initial centroid $c(0)$. The bias weighting represents semi-supervision for the unsupervised RBFN. The new centroid update function with semi-supervised RBFN is:

$$c(t+1) = (1-\gamma)\overline{X}^{+} + \gamma c(0) + \alpha_N \left(c(t) - \overline{X}^{-}\right) \tag{5}$$

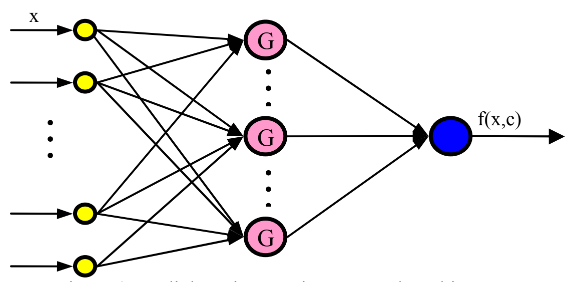



Figure 3: Radial Basis Function Network architecture.

*C. Automated Relevance Feedback*

Instead of human interaction, ARF uses the machine intelligence to evaluate the retrieval results and generate a new query vector for the relevance feedback, as illustration in Figure 2(b). In this paper, ARF uses a simplified texture in the query process – using second level Daubechies wavelet filter, and getting the mean and the standard deviation for each subband. Upon obtaining the retrieval results using the simplified texture features together with color and shape features, automated selection is made based on the similarity measure using the detail texture feature in [20]. In this paper, the machine controlled ARF is based on (1) the monothetic clustering approach [23] using the fuzzy c-means algorithm (2) the polythetic clustering approach using the SOTM algorithm. These techniques are used to identify the relevant image set $X^{+}$ and $X^{-}$ automatically. The clustering result is fed back to the RBFN system as described in the previous section.

The primary assumption of the ARF approach relies on the feature commonality of the irrelevant images compares to the relevant images (for example, all irrelevant images possess similar color histogram pattern). Failing to meet such criteria will result errors in grouping the relevant and irrelevant images. In practice, a large image database consists of different image categories with non-correlated feature descriptors.

During the feedback process using RBFN, the similarity measure is proportional to the sum of the distance measure for all the feature descriptor. The irrelevant images, while statistically possessing higher dissimilarity measure, may scatter over the $p$-th dimensional space in a non-uniform manner. For example, as illustrated in Figure 4, the monothetic clustering technique is likely to introduce positive and negative centroids that make the decisions inaccurate.

As shown in Figure 5, a polythetic approach makes the membership decision according to the distance measure to the cluster centroid. Instead of defining a fixed number of clusters as an exit condition [12][13], new centroids are generated dynamically if the similarity measure exceeds the threshold function, and these centroids are denoted as the groups of irrelevant images. Since the retrieved images are ranked according to the similarity measure from radial basis function, the ranking is weighted in the centroid updating process.

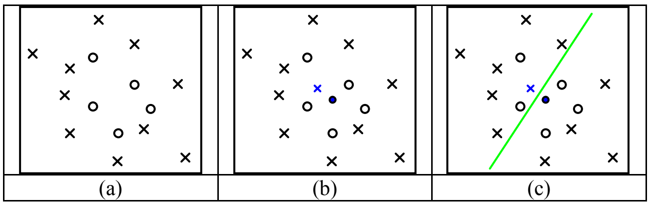



Figure 4: Example of monothetic clustering approach using the Fuzzy C-Means algorithm: (a) original dataset (b) computation of positive and negative centers using FCM (c) clustering using the monothetic clustering approach.

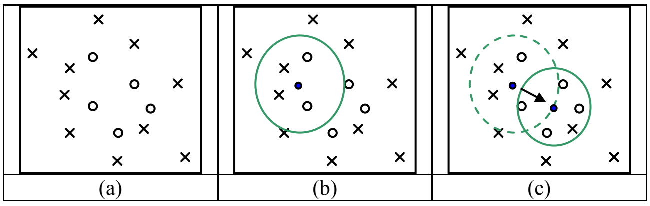



Figure 5: Polythetic clustering approach using the SOTM algorithm: (a) original dataset (b) clustering using SOTM at the first iteration (c) updated clustering using SOTM at the subsequent iteration.

*Fuzzy C-Means*

Fuzzy C-Means (FCM) is one of the most popular fuzzy clustering techniques [24]. The procedure of FCM is summarized below:

1. Given $n$ sample data $X$, number of clusters $c$, fuzzification factor $m$ and termination condition $e$>0.
2. Initialize the degree of membership matrix, $U$ of dimension $n$-by-$c$ according the constraints on $u_{ij}$.
3. Calculate the $c$ cluster centers based on $U$.
4. Compute the distance of each feature vectors to all the clusters centers based on the defined distance norm: $v_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m}$
5. Compute the degree of membership of all feature vectors in all the clusters:
$$u_{ij} = \left( \sum_{k=1}^{c} \left( \frac{d^2(x_i, v_i)}{d^2(x_i, v_k)} \right)^{\frac{1}{m-1}} \right)^{-1}$$
6. Continue step 3 if the maximum distance exceeds the predefined threshold $e$.

*Self Organizing Tree Map with Ranking Bias and Tree-Structure Decision Process*

An unsupervised neural network model, self-organizing tree map (SOTM) [25], is chosen to automate the feedback decision. SOTM is a polythetic clustering technique, and it has been applied in impulse noise removal [26] and image segmentation [25][27]. The detailed procedure for SOTM is summarized as below:

1. **Initialization:**
Randomly choose a root centroid node $w_j$, where $j$={1,2,…,$J$}. $J$ is the total number of centroid nodes which is set to 1 at initialization.
2. **Similarity matching:**
For each data point $x$, find out the winning centroid $j^*$ which has the minimal Euclidean distance.
$$w_{j^*}(t) = \arg\min_j \|x - w_j(t)\|, \quad j = 1,2,...,J \tag{6}$$
3. **Updating:**
Let $H(t)$ denotes the hierarchy control function for the level of the tree, which decreases in time and $H(t+1)= \lambda H(t)$ where $\lambda$ is the threshold decreasing constant and $0 < \lambda < 1$. Let $\alpha(t)$ denotes the learning rate which decreases in time, and $\alpha(t)=\alpha(t) /(\alpha(t)+0.5)$, $0 < \alpha(t) <1$. Let $\beta(x,t)$ denotes the ranking function which is inversely proportional to the ranking of the feature vector $x$ at iteration $t$.
**If** $\|x - w_{j^*}(t)\| \le H(t)$
**Then** update the winning centroid according to the reinforced learning rule:
$$w_{j^*}(t+1) = w_{j^*}(t) + \alpha(t)\beta(x,t)[x - w_{j^*}(t)] \tag{7}$$
**Else** a new centroid node at $x$ is created, and increment $J$ by 1.
4. **Continuation:**
Go to step 2 until no noticeable changes in the feature map are observed.

*D. Semi-Automatic Relevance Feedback*

Semi-automated relevance feedback is the combination of the interactive and the automated relevance feedback. As shown in Figure 6, an additional decision process determines whether the relevance feedback is interactive or automated. In this paper, the decision process is judged by a pre-defined number of interactive relevance feedbacks, followed by a handover to the automated relevance feedback.

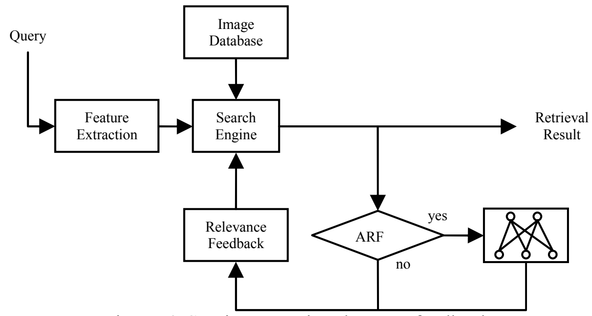


Figure 6: Semi-automatic relevance feedback.

## 3. CBIR over Centralized, Clustered, and Distributed Storage Networks

In this paper, we classify the networked CBIR systems according to the distribution of the feature database. The network topologies of centralized, clustered, and distributed P2P systems are illustrated in Figure 7.

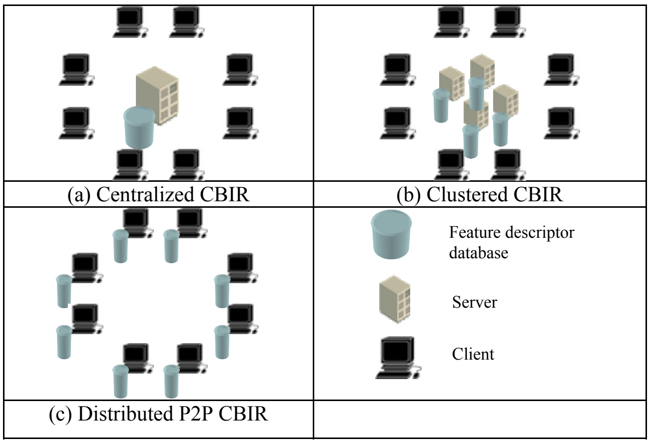


Figure 7: Networked CBIR system

*Centralized CBIR System*

The centralized CBIR systems keep the entire feature descriptor database in a centralized server. The real image content may or may not be storage on the same server. Similar to the conventional text-based search engine which performs the search based on the meta-tag database stored in the server, the centralized CBIR server retrieves the relevant content based on the feature-descriptor database. The drawback of the centralized CBIR system is the scalability issue to handle the growing retrieval requests and a larger image database.

*Clustered CBIR System*

To address the scalability issue for the centralized CBIR system, the feature descriptor database can be pre-clustered and store in different servers. In this paper, we use the k-means algorithm [23] to classify the entire feature descriptor database into $n$ non-overlapping sets of feature descriptors, which are distributed over $n$ servers for offloading the computational and the transmission cost. Each server in the cluster will pre-compute the centroid, which is the arithmetic mean of the feature descriptors store in this particular server.

During the query stage, the best query server is firstly identified from the similarity measure of the query feature descriptor and the cluster centroid using the nearest neighbor algorithm. Once the query server is identified, relevant content will be retrieved within the feature descriptor database store on this server.

*Distributed CBIR System*

Database storage on distributed servers had been applied in the industry to provide high availability (providing continuous service if one or more servers unintentionally out of service) and efficiency (access from the closest server geographically). P2P network is a special case of distributed storage network where each node in the P2P network behaves as a client as well as a server.

The underlying assumption of the multimedia content collection on a P2P node, or a peer, consists of limited categories, which associates to the users' habit on the data collection. Distributed CBIR system can benefit from such high correlation among certain peers, hence reduce the computational and the network cost by searching within a limited subset of peers. Each peer's image collection can be considered as a subset of the whole image database, and no assumption is made on the inter-dependencies or collaborating work between any two peers. Therefore, the overlap between can be used to improve the retrieval precision.

Each peer in the P2P CBIR system maintains two tables of neighbors: (1) the *generic neighbors* which typically represent the neighbors with the least physical hop counts, and (2) the *community neighbors* and common interest is shared among the community. The proposed distributed CBIR system consists of two stages of operation: *community neighborhood discovery* and *query within the community neighborhood.*

Community neighborhood discovery

As shown in Figure 8, a peer node originates the query request to its generic neighbors in the P2P network. Whenever a peer node receives a query request, it will (1) decrement the Time-To-Live (TTL) counter, and forward the request to the generic neighbors when TTL > 1, and (2) perform the content search within the peer's feature descriptor database. The retrieval results of each peer are transmitted to the original query peer directly in order to improve the efficiency.

Like most P2P applications, the proposed distributed CBIR system applies an application layer protocol, such that the system can be realized on today's Internet without modifying the underlying network infrastructure. The proposed query packet format to traverse through the P2P network is shown in Figure 9.

Once the destination peer receives the query and performs the feature descriptor lookup, it will issue a Query Reply to the query requester directly. The query results are in the form of filenames and distance. The actual file transfer is not part of the protocol, and protocols like HTTP, RTP, with or without encryption, may be applied depending on the application. Transferring the actual image content is coupled with the feature descriptor transmission, to eliminate the need to re-compute the feature descriptors upon receiving any new image. The proposed query response packet format to traverse through the P2P network is shown in Figure 10.

The query peer maintains a table of community neighbors based on past retrieval results to identify the peers which collects similar image database.

*Query within the community neighborhood*

Once the community neighbors are identified, subsequent queries will be made to limited peers within the community neighborhood. To improve the communication efficiency, instead of forwarding the request hop-by-hop in the community neighborhood discovery stage, direct communication between the peers is applied. The same packet format is used for Query and Query Response within the community neighborhood.

Each peer in the community neighborhood collects more than one category of images, with at least one common category as the requesting peer to satisfying the criteria to be listed in the community neighborhood. Therefore, the same image appears in multiple peers are likely belong to the common category in the community neighborhood. Let $Ret(I,P_n)$ denote the retrieved result using query image $I$ from peer $P_n$, where $P_n \in \{community\ neighborhood\}$. Let $N(\bigcap Ret(I,Pn))$ denotes the number of occurrences of each retrieved image $I$. Let $D_{N(I)}$ be the occurrences distance, which is calculated by normalizing $N(\bigcap Ret(I,Pn))$. Assign the weighting factor $Wp2p = [W_D\ W_N]$ to the feature distance $D_{feature}$ and distance measure according to the number of occurrences $D_{N(I)}$, respectively. The similarity ranking is:

$$Rank = W_{p2p} \cdot \left[D_{feature}\ D_{N(I)}\right]^T \tag{8}$$

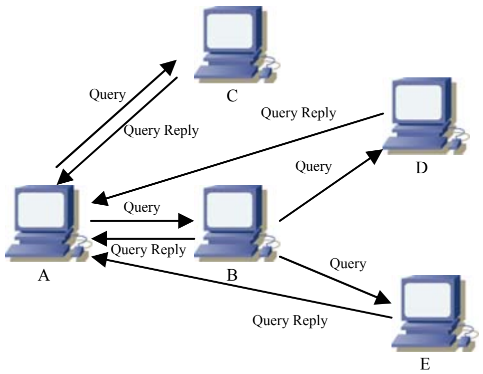


Figure 8: Neighborhood discovery

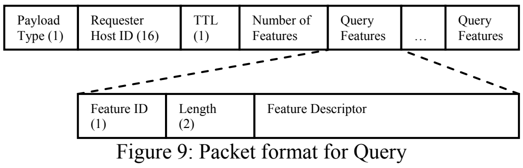


Figure 9: Packet format for Query

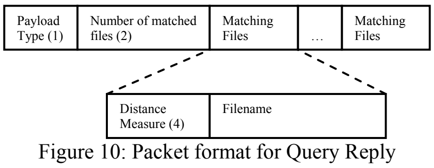


Figure 10: Packet format for Query Reply

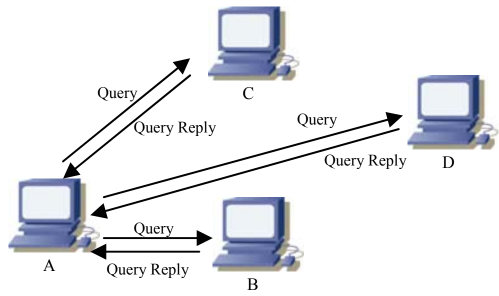


Figure 11: Search within community neighborhood

*Distributed CBIR with ARF*

While ARF reduces the need for human interaction for relevance feedback, integrating ARF to the proposed distributed CBIR framework introduces new challenges for the repeated requests to multiple peers, which consumes the network and the computational resources. To address this issue, an incremental searching mechanism is proposed to reduce the level of transactions between the peers.

As shown in Figure 12, peer A originates a query request to its nearest neighbor peer B. Peer B performs the query, and returns the top matched feature descriptors to peer A. Consequently, Peer A evaluates the retrieval results using the SOTM or the FCM algorithm, and generates a new feature vector using RBF as described in section II. New query request using the new feature vector will be sent to peer B, as well as expanding the audience set by forwarding the same query request to peer C. The query request and automated retrieval evaluation process is repeated until a pre-defined number of query peers is reached.

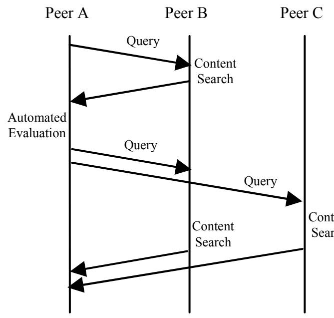


Figure 12: Incremental P2P CBIR system

*Offline feature calculation*

As described previously, on-the-fly feature calculation consumes high computational resources, which results significant delays for the content retrieval. The redundant online feature computation can be eliminated by the following procedures:

1. Each image stored in the P2P CBIR network is attached with its feature descriptor.
2. When a peer creates a new image in its database, the feature descriptors will be computed and attached to the image file before announcing the availability of the new image.
3. Any image transmission over the distributed P2P network will be coupled with the transmission of the image's feature descriptor.

Satisfying the above constraints decentralizes the feature descriptor database (FDD), which we address as the distributed FDD (DFDD). The DFDD on each particular network node is independent to the rest of DFDD, hence no impact on processing the distributed CBIR will be introduced if a network node joins or leaves the network. Nevertheless, the retrieval performance may be affected since the overall number of community neighbors is altered.

## 4. Experimental Results

For simplicity, the P2P network is constructed using an evenly distributed tree structure and each peer is connected to five other peers. The number of image categories that each peer possess follows normal distribution, with the mean $\mu_{cat}$=10 and the standard deviation $\sigma_{cat}$=2. The number of image per category is also normally distributed, with the mean $\mu_{images}$ =50 and the standard deviation $\sigma_{image}$=5.

The simulation is performed with the Corel photo image database, which consists of 40,000 color images. The statistical results are obtained by averaging the 100 queries in the categories of bird, canyon, dog, old-style airplane, airplane models, fighter jet, tennis, Boeing airplane, bonsai, and balloon.

Figure 13 shows the statistical analysis of the size of community neighborhood to the retrieval precision. We observe a steady increase for the retrieval precision against the size of the community neighborhood. Such characteristic serves the foundation of the proposed P2P CBIR system.

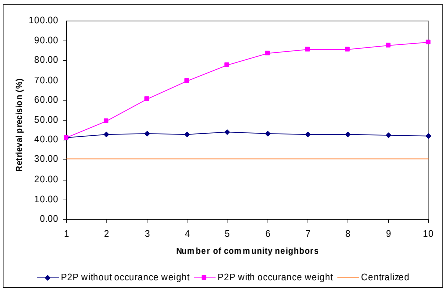



Figure 13: Statistical retrieval result for the proposed P2P CBIR system

To reduce the error propagation, Table 1 shows improved retrieval precision by introducing the bias weighting $\gamma$ to the query image for the RBF relevance feedback.

Since the output at each feedback stage is ranked according to the RBFN similarity measure, we observed that by adding the ranking bias $\beta$ to the automated selection process, the retrieval precision is improved.

| | Iter 0 | Iter 1 | Iter 2 | Iter 3 | Iter 4 | Iter 5 |
|---|---|---|---|---|---|---|
| $\gamma = 0$ | 44.75 % | 57.15 % | 68.3 % | 77.45 % | 79.5 % | 82.05 % |
| $\gamma = 0.2$ | 44.75 % | 58.15 % | 71.35 % | 77.9 % | 80.85 % | 83.25 % |

Table 1: Retrieval precision and the bias to the query image in the RBFN interactive relevance feedback

| | Iter 0 | Iter 1 | Iter 2 | Iter 3 | Iter 4 | Iter 5 |
|---|---|---|---|---|---|---|
| No $\beta$ | 44.75 % | 57.1 % | 68.6 % | 76.15 % | 79.2 % | 82.3 % |
| No $\beta$ | 44.75 % | 58.15 % | 71.35 % | 77.9 % | 80.85 % | 83.25 % |

Table 2: Retrieval precision for automated relevance feedback using SOTM

The statistical retrieval result in Figure 14 indicates that statistically SOTM outperforms FCM for the automated machine controlled clustering for relevant and irrelevant images automatically. Note, since the feedback is automated, higher iteration order reflects higher retrieval precision at the cost of the computational and the network resources.

The same experiment is repeated for the clustered CBIR system, where the image database is pre-classified into 10 clusters using the k-means algorithm. Prior to the similarity match process, the best cluster to perform the retrieval is determined from the query feature descriptor and the cluster centroid using the nearest-neighbor algorithm. As shown in Figure 15, the proposed clustered CBIR system trades off 5.75% retrieval precision in average for offloading the computation with an order $O(1/N)$ where $N$=10.

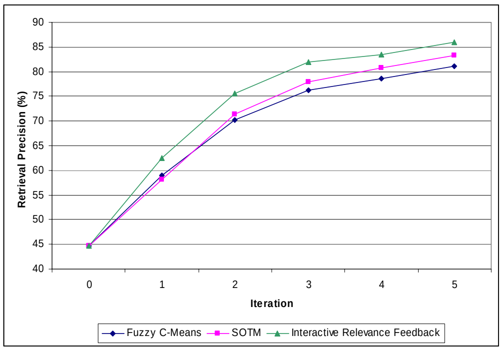



Figure 14: P2P CBIR ARF with FCM and SOTM

The inter-dependence between each individual image database can be used to improve the retrieval precision for centralized CBIR system, using the same algorithm proposed for distributed CBIR system. While the centralized CBIR system typically includes higher order of database, higher diversity is expected. In our simulation, the number of image per category is also normally distributed, with $\mu_{cat}$=20, $\sigma_{cat}$=5, $\mu_{images}$ =50 and $\sigma_{image}$=20.

Comparisons between centralized CBIR, the clustered CBIR, centralized CBIR accounting inter-dependencies between individual databases, and the distributed CBIR, are illustrated in Figure 15. Accounting the overlap between relevant databases used for distributed P2P CBIR, as described in section 3, we observed improvement in the retrieval precision for centralized CBIR with similarity weighting.

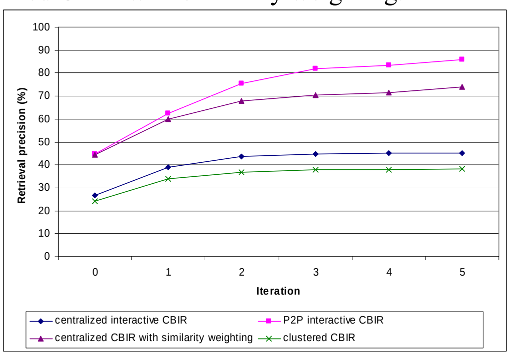



Figure 15: Interactive relevance feedback using Radial Basis Function Network with bias to the query image

Figure 16 compares the experimental results for the semi-automated relevance feedback and the interactive relevance feedback over the proposed P2P CBIR system. The x-axis indicates the *n* interactive relevance feedback performed. For the semi-automated relevance feedback, the plot is coupled with 5-*n* automated relevance feedback. The interactive relevance feedback (the bottom plot) does not involve automated relevance feedback. We observe a significant increase of retrieval precision by including additional automated relevance feedback while *n* is small (an improvement of 38.5% when *n*=0). Increasing the number of *n* in semi-automated relevance feedback slightly improves (an improvement of 2.8% when *n*=5 compares to n=0). The two plots converges to the same value since semi-automated relevance feedback is equivalent to interactive relevance feedback when *n*=5 in our study.

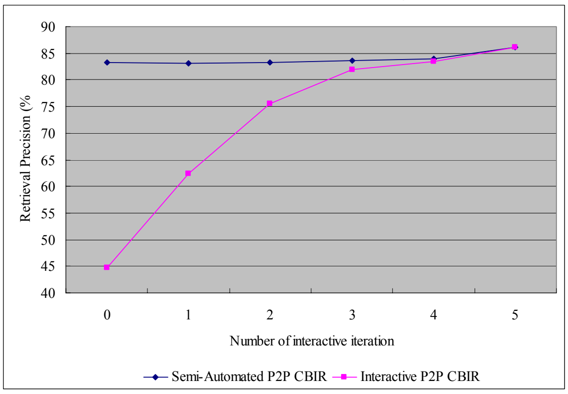



Figure 16: Semi-automated relevance feedback and interactive relevance feedback over the P2P CBIR framework

Finally, the sample screenshots of the a query for an airplane, from the centralized database, with the first and fifth iteration of interactive relevance feedback, and with ARF on the distributed P2P CBIR system, are shown in Figure 17 to Figure 20, respectively:

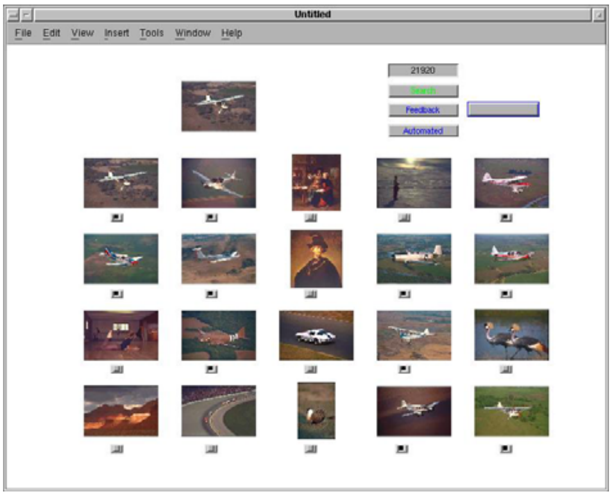



Figure 17: CBIR from a centralized database, the retrieval precision is 55%

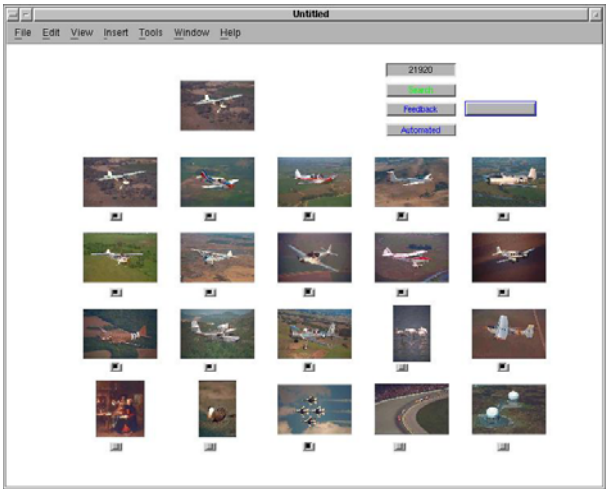



Figure 18: Relevance feedback with single iteration, the overall retrieval precision is 70%

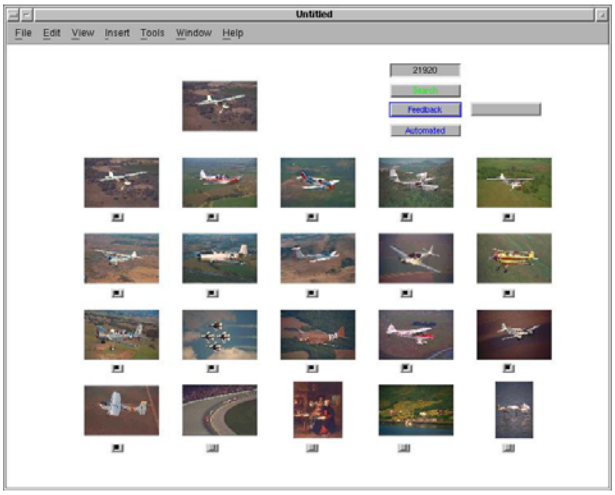



Figure 19: Relevance feedback with five iterations, the overall retrieval precision is 80%

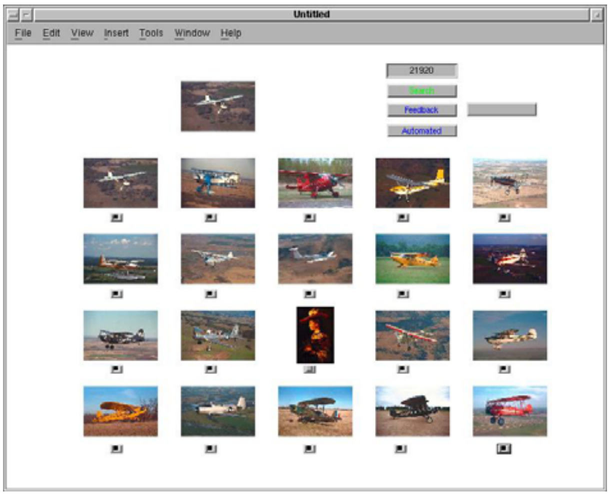



Figure 20: P2P CBIR with automated relevance feedback, the overall retrieval precision is 95%

## 5. Conclusion

In this paper, we present the analysis of the CBIR system with the human controlled and the machine controlled relevance feedback, over different network topologies including centralized, clustered, and distributed content search.

In our experiment for the interactive relevance feedback using RBF, we observe a higher retrieval precision by introducing the semi-supervision to the non-linear Gaussian-shaped RBF relevance feedback.

We study the automated relevance feedback technique over the proposed CBIR system using (1) the monothetic clustering approach using the FCM algorithm, and (2) the polythetic clustering approach using the SOTM algorithm. Our simulation demonstrates that the polythetic approach statistically outperforms the monothetic approach.

To address the scalability issue for centralized CBIR system, we propose the clustered CBIR system. The clustered CBIR system helps offloading the computational and networking cost for the centralized server with an order of 10, by trading off the retrieval precision by 5.75%.

We introduce an innovative distributed CBIR system, with the offline feature calculation and the hierarchical searching process. We have shown that grouping the peers into community neighborhood according to the common interest, is an effective way for the content retrieval over a distributed storage environment. We observe the occurrences weighting helps improving the retrieval precision for the P2P CBIR system. Further more, increasing the size of community neighborhood also improves the retrieval results significantly with the occurrences weighting.

From the simulation, we also observe that (1) with the same level of manual operation, the semi-automated relevance feedback results an improved retrieval precision by including additional ARF to a CBIR system, and the performance enhancement is significant when the number of interactive iteration is small; (2) increasing the interactive iteration (with the cost of increased manual operation) in the semi-automated relevance feedback slightly improves the retrieval precision. Our simulation results demonstrate that the semi-automated relevance feedback technique is a cost-effective methodology for CBIR over distributed P2P network.

In this paper, the proposed distributed CBIR system takes the feature descriptors from unprocessed query image. One popular approach in CBIR is to segment the query image and allow the user to identify the region of interest (ROI), and this approach is commonly known as the region-based or object-based CBIR [28][29]. Integration of region-based retrieval to distributed CBIR system is a foreseeable future work for this project.

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