The Application of User Log for Online Business Environment using Content-Based Image Retrieval System

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Abstract

Over the past few years, inter-query learning has gained much attention in the research and development of content-based image retrieval (CBIR) systems. This is largely due to the capability of inter-query approach to enable learning from the retrieval patterns of previous query sessions. However, much of the research works in this field have been focusing on analyzing image retrieval patterns stored in the database. This is not suitable for a dynamic environment such as the World Wide Web (WWW) where images are constantly added or removed. A better alternative is to use an image's visual features to capture the knowledge gained from the previous query sessions. Based on the previous work [1], the aim of this paper is to propose a framework of inter-query learning for the WWW-CBIR systems. Such framework can be extremely useful for those online companies whose core business involves providing multimedia content-based services and products to their customers.

1 Introduction

Image provides an important dimension in e-Business. It provides much richer information and content to the clients and users than text alone. Due to the explosion in the number of images available in digital format, it has become an easily obtainable item for personal, commercial or industrial use. Especially with it's ease of transfer and exchange via the Internet, image has now become a common commodity in the context of e-Business for B2C, B2B, P2P and C2C transaction

In general, an image retrieval system is a computer system for browsing, searching and retrieving images from a large database or multiple databases of digital images. While such activities can be easily based on textual descriptions of the images in the form of keywords or "tags", manual naming and labeling of the images is laborious and time-consuming. It can also be ambiguous as different people may interpret the key words or features differently. Content-based image retrieval (CBIR) aims at reducing the need for textual description and to provide the most appropriate images automatically. In addition, Relevance Feedback (RF) can be used to refine the search and to define the scope of the search or retrieval.

CBIR system has been one of the most active areas of research in recent years [2]. Most of research attentions have been focused on retrieving images based on image query. In these studies, RF is commonly used as a communication tool for interacting with the system user. In machine learning, RF can be classified into two learning strategies, namely, the intra and inter query learning. Intra-query is a short term query learning approach which only focuses on improving the accuracy of retrieval in a single retrieval session. On the other hand, inter-query is a long term learning approach in analyzing the search pattern from the given search history. By accumulating the previous search sessions, inter-query learning aims at enhancing future retrieval performance.

To the authors' knowledge, most of these studies have been focusing on analyzing the relationship between images based on the user's retrieval patterns. The major short fall of this approach is that it assumes the database to be static. This approach does not perform well in a dynamic environment where users constantly add and remove images from the database. This is typically the case for images in WWW. In a web environment, images posted on the Internet are frequently altered or updated by the web master to either attract or convey sales and marketing messages to prospective target audience. In the case of an information service provider such as ESPN (www.espn.com), different images are posted on its home page on a daily basis to keep readers keen and interested with news highlight of the day. In the context of a retail

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shop like Chico's (www.chicos.com) that features online catalogue, images are updated on a regular basis to achieve attractiveness and retain attention of existing customers. In these scenarios, it will be difficult for any CBIR systems to keep track and index the images. A better approach would be to capture the retrieval history via the visual features of the retrieved images. An advantage to this approach is that the management and tracking of images are no longer required since the user retrieval pattern is now being captured by the visual features common to the selected images.

Based on the previous works by [1, 3, 4], this paper extends the existing frameworks by broadening the previously proposed WWW-CBIR system to include a long-term learning component. This paper first provides a brief review on some of the existing CBIR systems and approaches used in inter-query learning by content-based image retrieval systems. The paper also provides a description of the proposed framework. Results from experiments conducted on the proposed method are reported. Finally, a conclusion is drawn based on the experimental findings.

2 Background

2.1 Content-Based Image Retrieval System

Researchers have achieved certain degree of success in retrieving images based on the low level image features. Veltkamp and Tanase [5] provide a comprehensive report on various image retrieval systems commercially available or in prototype research stages. Their report shows that most of these systems use a very similar architecture design. Systems such as QBIC [6], GIFT [7], MARS [8] and PhotoSeek [9] all need to pre-process the images stored in their database. This is done so that the images can retrieve by their visual content. To do this, these images are required to be pre-processed by feature extraction algorithms, the extracted features are then organized as a flat feature vector for distance similarity calculation. The feature vector is often acted as the index key to these images. In these systems, one can improve on the retrieval speed by implementing an efficient indexing structure. The tree like structure is effective for vector space indexing. Interested readers can refer to [2] for a comprehensive overview of the CBIR systems.

The WWW-CBIR is an extension from the original CBIR systems. While the original system operates mostly in a closed-environment, the WWW-CBIR systems are part of the Internet. This difference implies that, at the architecture level, at least an extra module is required for interfacing with the Internet. Generally, there are two approaches in designing the WWW CBIR system. Firstly, systems such as PicToSeek [10], WebSeek [11] and ImageRover [12] uses web-crawler robots to traverse through the Internet for image collection. Alternatively, instead of collecting images from other sources, popular search engines such as Yahoo, AltaVista, Lycos and Google only process images from the Web sites that are registered with them. To a certain degree, these systems are comparable to the systems described previously with the exception that they do not have a web-crawler agent for Internet traversing. Similar to the original systems, the images stored in both types of systems are to be further classified for indexing purpose. These images are either indexed visually or semantically. Text description is the common way of indexing the images semantically, while visual indexing method is similar to the method used by the original system. One can see that if the system is to be able to retrieve images via visual content, visual features become the key to an accurate retrieval. A currently popular research direction is to provide feedback mechanisms to interact with users in an attempt to capture the important visual features of the user's target images.

2.2 Inter-Query Learning

From reported literatures, inter-query learning can be classified based on two approaches. The first approach's origin is from the traditional text search and retrieval systems. In this approach, the goal is to analyze the relationship between images and their related queries through the user's retrieval patterns. It is assumed that if there are two identical query retrieval patterns, then the images involved in the queries must be semantically similar. Techniques such as latent semantic indexing (LSI) [13] and statistic correlation [14] are the popular choices in this approach. Other reports [15-17] have extended this approach further by attempting to analyze the hidden semantic relationship among the image groups that are indirectly related to each other. The weakness in all of the mentioned approaches is that the image database has to be relatively static. To illustrate the point, as mentioned before, a 2-dimensional table is commonly used by previous approaches to store the semantic score of each image against one another. Under this approach, the semantic relationship between an image and all the retrieved images can be calculated by averaging the semantic score between the image and all other retrieved images. However, this scheme is not applicable in scenarios where the image in consideration is a new addition to the database and semantic scores for the image is not yet calculated. Thus, this re-iterates the point that such approach is not suitable for a dynamic environment

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such as the WWW.

The second inter-query approach is based on the feature vector model approach. The idea behind this approach is to extract the visual information of the image such as color, texture and shape and represent in a one dimensional vector format. The scale of the feature vector coordinate is then transformed to bring similar images closer to each other while pushing the negatively labeled images further apart. The transformation of the feature vector coordinate may be done through a weighting scheme or the kernel matrix transformation. Figure 1 depicts a case of performing non-linear data transformation to a new feature space where the two groups of samples can be separated linearly. The use of non-linear data transformation in feature vector model has been used by many researchers in short-term learning. In the case of long-term learning, the retrieved images from a query session are often captured as clustered group. The information on the retrieved images is then stored in the "user log". This approach rules out the need of "memorizing" actual retrieval relationship between the actual images and the previous queries.

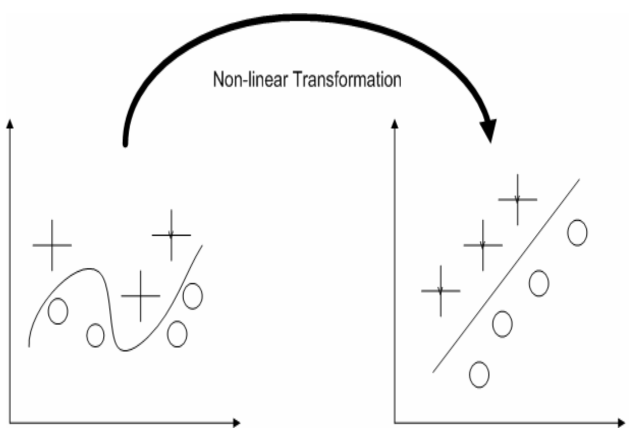

Figure 1 Illustration of Non-linear Data Transformation

3 Proposed Framework

3.1 Previous Work

3.1.1 Short-Term Learning

In [3], a CBIR framework for WWW was introduced. In that paper, it was proposed that the system acts as an independent agent from the WWW search engines. Instead of storing the images in a database, the system only has to analyze the collected images from other search engines and outputs only those are relevant. Like any other search engines, the image retrieval process is triggered by search query performed by the user. This system does not require a large database, but at the cost of slower feedback response time. To accelerate the retrieval process, the paper suggested a visual feature selection framework to accelerate the image processing time. The feature selection was successful in improving the retrieval speed without sacrificing too much accuracy. The accuracy retrieval performance feature selection framework was later improved by replacing the multi-layer kernel structure with a flat cascade structure [4].

3.1.2 Long-Term Learning

While the above works focused on the short-term learning, [1] concentrates on the issue of long-term learning. It is also known as *inter-query* learning. The proposed long-term learning framework is an extension from the short-term learning approach, called Kernel-Biased Discriminant Analysis (KBDA), as proposed by Zhou and Huang [18]. In [1], a cluster is form after each retrieval session. The cluster is described by the feature space created by KBDA and the boundary of the cluster is defined by the furthest positive labeled image from the positive centroid. Since the cluster contains the visual information common to the previously selected positively labeled images, it is assumed that the two retrieval sessions are similar when the majority of the images gathered from the short-term learning algorithm fall within the boundary of a selected cluster. Thus, retrieval performance will be improved by using the selected cluster as a new query point to subsequence retrieval cycles.

In recent years, support vector machine (SVM) has been a popular tool in machine learning related applications. However, after a close examination on the theory of SVM, it is decided that such approach may not be best suited for the visual feature based inter-query learning system. Instead, statistical discriminant analysis or more specifically KBDA has been selected as the machine learning tool for this framework. More detail discussion on this decision is followed in the next section.

3.2 SVM vs Statistical Discriminant Analysis

In the feature vector approach, support vector machine (SVM) [19, 20] has been reported as one of the most popular machine learning tools for image clustering in inter-query learning. This is primarily due to its ability to analyze non-linearly related data with small sample size. In short, SVM is a way of learning non-linearly related samples by performing non-linear transformation so that the samples can be linearly separated. One may view this as a way of classifying non-linearly related data. The aim is to find the optimal separating hyperplane with minimal classification error. The classification is based on linear function expressed as:

$$w.z + b = 0 \quad (1)$$

where the parameter w is the vector normal to the hyperplane, and b is the bias scalar factor. According to Vapnik [21], using Lagrange multipliers, the decision function for the optimal classification can be expressed as:

$$\begin{aligned} & f(x) \\ & = w.z + b \\ & = \sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b \end{aligned} \quad (2)$$

where α_i is the Lagrange multiplier and it is used to separate the two labeled samples. The parameter y_i is the actual label for each sample. For a two class classifier, y is usually in the form or -1 or 1. Lastly, $K(x_i, x)$ is the kernel function in the input space that computes the dot product of the two samples in the feature space.

From expression (2), one can see that the Lagrange multiplier α_i along with the kernel function are the two major factors in determining the discriminant ability of the given samples. The actual values of the Lagrange multiplier can be determined by minimizing the classification errors of the given samples. Thus, the values of the Lagrange multiplier are dependent on the content of the given samples. The values of the multiplier have to be re-calculated every time when the content of the sample changes. It can not be updated with direct matrix algebra calculation. Reason being, the computation of α_i is often non-linear. A characteristic of non-linear transformation is that the outcome may often result in loss of information. In turn, such computation is usually irreversible. The exact original sample may never be recovered once the samples are transformed.

Without the original samples, one can only approximate the original input feature vectors by performing non-linear data approximation. One may settle for an approximate solution pre-image calculation [22, 23]. However, such approach is often computational intensive. The approach may also be conducted at the cost of system response time to user. Furthermore, pre-image calculation often implies introducing extra parameters into the system which result in additional complexity. Thus, one can see that SVM may not be best suited for the proposed WWW-CBIR system.

Statistical discriminant analysis on the other hand is free from such issue. The idea of KBDA [18] is to transfer data from the original space to a new feature space that can best discriminates the positive images from the negative samples given. This is done by applying a set of weight vectors W that maximizes the ratio between the positive covariance matrix S_x^ϕ and the biased matrix S_y^ϕ.

$$W_{opt} = \arg\max_{w} \frac{\left\| W^T S_y^\phi W \right\|}{\left\| W^T S_x^\phi W \right\|} \quad (3)$$

One can view the above expression as a problem of generalized eigen-analysis where the optimal eigen-vectors associated with the eigen-values are the transformation matrix for the new feature space. In KBDA, the positive covariance matrix S_x^ϕ and the biased matrix S_y^ϕ are defined as:

$$S_y^\phi = \sum_{i=1}^{Ny} \left(\phi(y_i) - m_x^\phi\right)\left(\phi(y_i) - m_x^\phi\right)^T \quad (4)$$

$$S_x^\phi = \sum_{i=1}^{Nx} \left(\phi(x_i) - m_x^\phi\right)\left(\phi(x_i) - m_x^\phi\right)^T \quad (5)$$

where $\{x_i = x_i, \ldots, x_{N_x}\}$ and $\{y_i = y_i, \ldots, y_{N_y}\}$ denote the positive and negative examples respectively. The variable N_x and N_y are the respective total number of given positive and negative samples. The mean vector of the positive transformed samples is defined as m_x^ϕ, and finally, Φ is the kernel mapping function.

By examining expressions (3), one can see that the transformation matrix W cannot be directly updated by the feedback result. However, since the transformation matrix is derived from the covariance matrix as shown in expression (4) and (5), the updating can be done through these two equations. Through manipulation of the matrix, the two equations can be re-written as:

$$S_x = \left(\frac{1}{N_x} \sum_{i=1}^{Nx} x_i x_i^T \right) - m^\phi{}_x m^{\phi T}{}_x \quad (6)$$

$$S_y = \left(\frac{1}{N_y} \sum_{i=1}^{Ny} y_i y_i^T \right) - m^{\phi}{}_y m^{\phi}{}_x^T - m^{\phi}{}_x m^{\phi}{}_y^T + m^{\phi}{}_x m^{\phi}{}_x^T$$
(7)

where $m^{\phi}{}_y$ denotes the mean vector of the negative samples, also known as the negative centroid.

By examining equations (6) and (7), it is obvious that the covariance matrix S_x and S_y are defined by the following expressions: $\sum_{i=1}^{Ny} y_i y_i^T$, $\sum_{i=1}^{Nx} x_i x_i^T$, and, the number of positive samples, the number of negative samples and the centroids of the positive and negative samples. All of these variables can now be updated from the given the sample data. Hence, unlike SVM, no pre-image calculation is need. The parameters can be easily updated with the following equations:

$$\sum_{i=1}^{Ny} y_i y_i^T = \sum_{i=1}^{O\_Ny} O\_y_i O\_y_i^T + \sum_{j=1}^{A\_Ny} A\_y_j A\_y_j^T \quad (8)$$

$$\sum_{i=1}^{Nx} x_i x_i^T = \sum_{i=1}^{O\_Nx} O\_x_i O\_x_i^T + \sum_{j=1}^{A\_Nx} A\_x_j A\_x_j^T \quad (9)$$

$$new\_m_x = \frac{O\_m^{\phi}{}_x * O\_N_x + A\_m^{\phi}{}_x * A\_N_x}{O\_N_x + A\_N_x} \quad (10)$$

$$new\_m_y = \frac{O\_m^{\phi}{}_y * O\_N_y + N\_m^{\phi}{}_y * N\_N_y}{O\_N_y + N\_N_y} \quad (11)$$

where variables with "*O_*" prefix implies the original variable and prefix *"A_"* represents the newly acquire data.

3.3 Overview of the Proposed WWW System

The proposed framework is based on the previous works as reported in [1, 3, 4]. The newly proposed framework extends the WWW-CBIR framework as proposed in [3] and the improvement made in [4] with the inter-query learning framework as reported in [1]. Figure 2 depicts the framework for the newly proposed WWW-CBIR system. It shows that the retrieval process begins by user entering a search phrase or keyword into the system's user interface. The system then alias with Internet search engines to download all the images related to the search phrase. Using the rank provided by the search engines, the system will then retrieve the first batch of images. User will then select the relevant images. From the labeled samples, the system will rank the images via the stated short-term learning [4] and the long-term learning algorithm [1]. The ranked images are then merged by selecting the top ranked images from each learning framework. The merged results will again be displayed to the user who is ready for the next retrieval cycle. At the end of the retrieval session, the retrieval information will be captured and saved in the user log file.

4 Experiment Results

4.1 Prototype System

To evaluate the performance of the proposed approach, the authors have designed and implemented a prototype CBIR system using Matlab simulation software toolbox. This prototype is only a *closed* system, implying that the system is not yet connected to the Internet. The data samples used in the experiment are based on the Corel image database.

This prototype system provides user with the ability to query the database with an image sample. After the first retrieval iteration, users can select the relevant images while ignoring the non-relevant ones. The system will label the selected images as positive while treating the ignored ones as negative. The retrieval procedure of the prototype system is as follows:

1. Inputs a query image.
2. The visual features of the query are extracted by the system.
3. All images in the database are sorted in ascending order based on the distance of dissimilarity.
4. Display the top 20 images with the highest rank.
5. Selects the positive images and the rest will be automatically labeled as negatives.
6. Use the labeled images, perform the proposed decision algorithm,
7. Create new queries for image retrieval.
8. Rank and display the top 20 images that have not been labeled by the user.
9. Go back to step 5 for the next retrieval cycle.
10. Update the user log at the end of the retrieval session.

4.2 Experiment Environment

In order to test the performance of the proposed approach, two systems have been implemented. They are (i) the proposed approach and (ii) a short term learning framework based on [4]. To evaluate the validity of the experiment, the environment and parameters used by all three systems are identical. The statistical discriminant analysis technique, image features, the generalized eigenvector calculation methods are the same and the same parameters are also used in the kernel transformation algorithm for all three systems. In this experiment, KBDA [18] is selected as the statistical discriminant analysis technique. As for the visual features, four features have been selected. They are based on analysis of shape [24], texture [25], RGB and HSV color histogram of the images. Each feature comprises a number of elements. A total number of forty-eight feature elements have been used. Lastly, Gaussian Radial Basis Function (RBF) is selected as the kernel transformation matrix for the KBDA approach. This is based on the findings that literatures for CBIR systems [18, 26] have reported that RBF yields the best accuracy performance out of all the other kernel transformation approaches.

4.3 Experiment Data

In this experiment, 500 images of the Corel image database were used. Within these images, 250 images are classified under five different themes. Each theme contains 50 images. The tests were generated by randomly selecting 300 positive labeled images from each theme as input entry point to the system. The same data set were then carried out in the second test with a different random sequence. This is done to ensure the consistency of the test results.

The retrieval accuracy is used as the main factor for comparing the performance of the two frameworks. In this test, the retrieval accuracy is defined as:

$$accuracy = \frac{N_i}{T_i} \qquad (12)$$

where N_i is the number of relevant images selected for theme i, and, T_i is the total number of relevant images for the same theme. This is also commonly known as *precision.*

4.4 Experiment Results

Figure 3 depicts the average retrieval accuracy between the original framework and the newly proposed framework. It shows that with the exception of "bird", the retrieval performance of the newly proposed framework is more superior to the original framework. As for the theme "bird", the retrieval performance of the original framework is only marginally better than the newly proposed framework. The results show a general improvement in the retrieval performance in newly proposed framework.

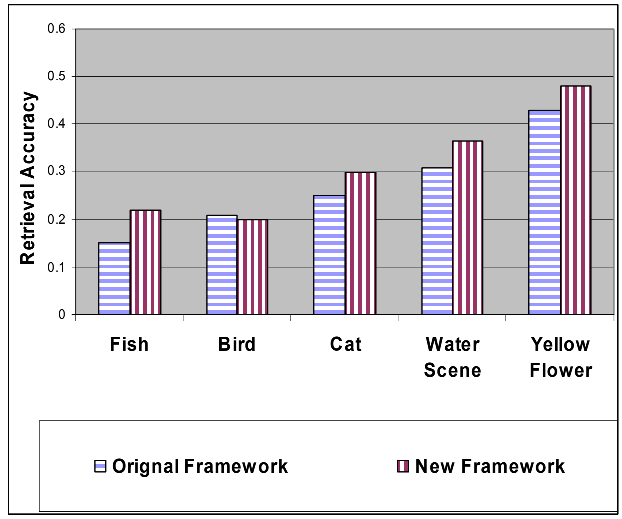

Figure 3. Retrieval Accuracy between the Original and New Framework

5 Implications for Practice

The test results as shown in Section 4.4 indicate the potential of the proposed framework for the WWW applications. The improvement in the retrieval accuracy of the proposed framework over the short-term learning framework implies that the framework possess the ability to learn from the experience gain from the previous retrieval sessions. From a commercial perspective, such framework has the potential to improve user's comfortability, which may lead to usage loyalty toward the system. Given the clutter of information presented on the web, such accurate and easy access to image search history would be highly valued in the online community.

6 Conclusion

A conceptual WWW-CBIR with long-term learning framework has been proposed in this paper. The proposed framework is primarily designed to capture the relationship between images and previous queries without the needs of "memorizing" actual retrieval relationship between the actual images and the previous queries. The experiment results have shown to support this goal.

This paper has introduced a framework designed for online companies that provide services such as collecting and providing desired images to their customers. The inter-query learning module as introduced in this paper has the potential of improving customer or user's loyalty towards the system.

The framework has only been tested in closed database environment. Future direction of this study would be to test the applicability of the framework in a less controlled environment such as an online retail shop, an online photography company, or an online art dealer. Such study would also be suitable for online portal systems where it act as agent for buyers and sellers of images or information that comes in the form of images.

The proposed WWW-CBIR framework for this study only focuses on capturing the user image retrieval pattern base on the visual pattern common to the positively selected images. Another direction is to extend such framework by associating search keywords to selected clusters used during the image retrieval session. The keyword may also link to a word dictionary database to further improve the rigor of keywords used in the search session.

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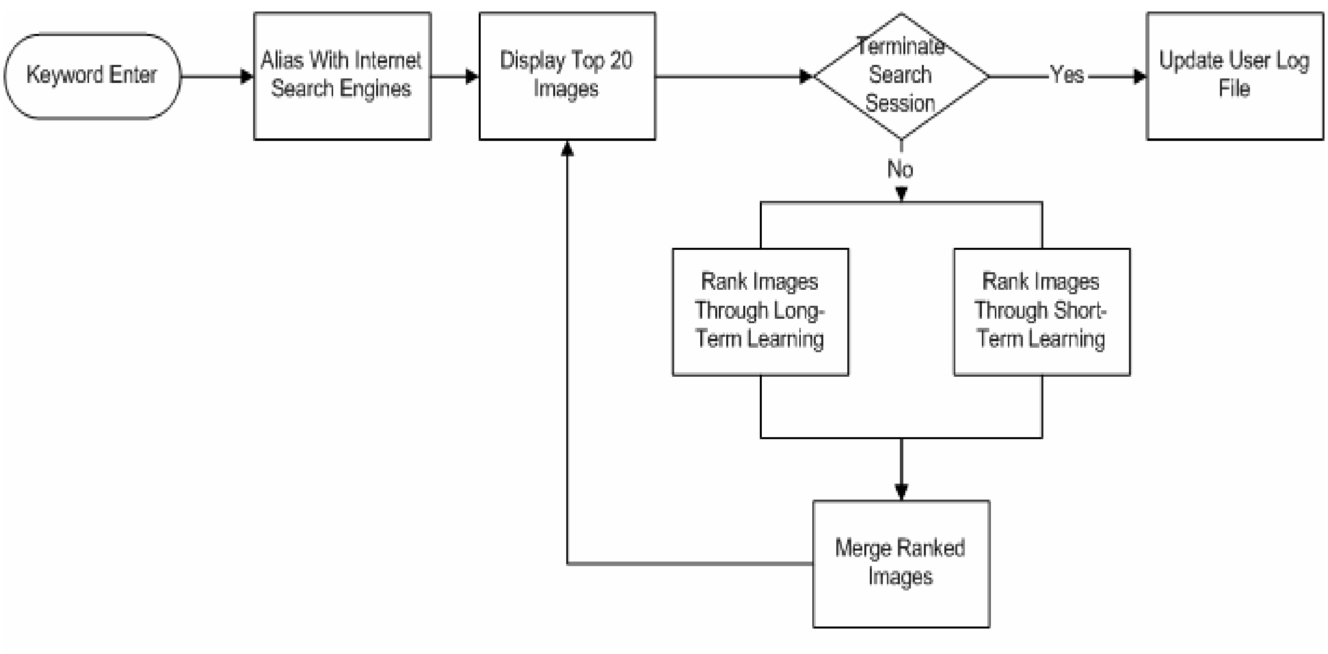

Figure 2. Framework for the proposed WWW-CBIR.