A Survey on Different Relevance Feedback Techniques in Content Based Image Retrieval

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Abstract - *The conventional image retrieval methods like Google, Bingo, Yahoo are based on the on textual annotation of images to access the large collection of relevant database images. Then Content Based Image Retrieval (CBIR) is a technique, which takes visual contents of image to retrieve relevant images from large databases. In Content Based Image Retrieval, there is a semantic gap between the low level features and high level semantic concepts. Different relevance feedback techniques bridge this semantic gap. In this paper analyse different subspace learning based relevance feedback algorithm to retrieve images.*

Key Words: Content based image retrieval, Semantics gap, Relevance feedback, Feature modification, Subspace learning

1. INTRODUCTION

Content Based Image Retrieval (CBIR) has attracted much attention during the past decades. CBIR is an image retrieval techniques used to retrieve relevant images without using any image annotations. CBIR systems uses visual content of an image such as color, shape and texture features as image index [9]. The CBIR systems adopt the Euclidean distance metric in a high dimensional low level visual feature space to measure the similarity between the query image and the images in the database. But the Euclidean distance metric in a high-dimensional space is usually not very effective due to the gap between the low-level visual features and the high level semantic concepts [8]. Thus performance of CBIR system is poor due to the semantics gap between the input image and low level visual features [9]. The effect of semantics gap is avoided by using relevance feedback technique.

Relevance feedback is a powerful tool and online learning to retrieve most relevant images. This strategy ask user to give some feedbacks on the results returned in the previous query round and come up with a better result based on these feedbacks. A variety of relevance feedback techniques designed to bride the semantics gap between low level visual features and high level semantic concept of each image [7]. The general process of Relevance Feedback is as follows: First user labels a number of relevant images as positive feedback and a number of irrelevant images as negative feedback from retrieved images. Then the CBIR system then refines its retrieval procedure based on these labeled samples. These processes carried out iteratively. RF techniques are classified into two categories: that is query movement and biased subspace learning. In this biased subspace learning, all positive samples are alike and each negative samples in negative in its own way [8].

2. LITERATURE SURVEY

In [1] Anelia Grigorova, Francesco G. B. De Natale, Charlie Dagli, Thomas S. Huang, Life Fellow, presents a feature adaptation techniques to retrieve more relevant images. It is an effective feature space dimension reduction according to user's feedback, but also improves the image description during the retrieval process by introducing new significant features. FA-RF uses two iterative techniques to make use of the relevance information that is query refinement and feature re-weighting. For the adaptation of across RF uses the descriptions of both relevant and irrelevant image, as well as their number and proportions. The query image is located near to the boundary of the relevant cluster in the feature space then the system contains few relevant images. Thus the query refinement mechanism is useful to move the query towards the middle of the cluster of relevant images in the feature space. This FA-RF performs very well in terms of capability in identifying most important features and assigning them higher weights compared with classical feature selection algorithms. Also maintain compact image description. The main drawbacks are less efficient for large databases. There is also needs an efficient feature extraction algorithm.

In [2] Mohammed Lamine Kherfi and Djemel Ziou proposed a new RF framework that combines the advantages of using both the positive example (PE) and the negative example (NE). This method learns image features and then applies the results to define similarity measures that correspond to the user judgement. The use of the NE allows images undesired by the user to be discarded, thereby improving retrieval accuracy. This method tries to learn the weights the user assigns to image features and then to apply the results obtained for retrieval purposes. It also reduces retrieval time. It clusters the query data into classes and model missing data, and support queries with multiple PE and/or NE classes. The main function of this method is that it assigns more importance to features with a high likelihood and those which distinguish well between PE classes and NE classes. The drawbacks are small sample problem. Also the use of PE is sufficient to obtain satisfactory results.

In [3] Dacheng Tao, Xiaoou Tang, Xuelong Li and Xindong Wu, presents an Asymmetric Bagging and Random Subspace based Support Vector Machine (ABRS-SVM) to solve the problems of SVM in image retrieval and over fitting problem.

The bagging incorporates the benefits of both bootstrapping and aggregation. In bootstrapping multiple classifiers can be generated by training on multiple sets of samples that is random sampling with replacement on the training samples. Aggregation of the generated classifiers then is implemented by majority voting. The bootstrapping is executed only on the negative feedback samples because there are far more negative feedback samples than the positive feedback samples. Each generated classifier is trained on a balanced number of positive feedback samples. The asymmetric bagging strategy solves performance degradation of SVM classifier. The small sample sized problem is solved by using Random Subspace based SVM. RSM performs the bootstrapping in the feature space. The over fitting happens when the training set is relatively small compared with the high dimensional feature vector. In order to avoid over fitting, sample a small subset of features to reduce the difference between the training data and the feature vector length. Using this random sampling method, first construct a multiple number of SVMs and then combine these SVMs to construct a more powerful classifier. The main drawback of this system is it does not handle unlabeled samples.

In [4] Ja-Hwung Su, Wei Jyun Huang, Philip S. Yu, Fellow, and Vincent S. Tseng, proposed a Navigation Pattern based Relevance Feedback (NPRF) achieve high efficiency and effectiveness with the large scale image data. Also reduces number of iterative feedbacks to produce refined search results. The iterative feedbacks are reduced substantially by using the navigation patterns discovered from the user query log. This NPRF approach is divided into two operations that is the online image retrieval and offline knowledge discovery. NPRF Search makes use of the discovered navigation patterns and three kinds of query refinement strategies such as Query Point Movement (QPM), Query Reweighting (QR), and Query Expansion (QEX). The query image is submitted to this system, and then the system first finds the most relevant images and returns it. This process is called initial feedback. Next, the positive samples picked up by the user is given to the image search phase including new feature weights, new query points and user's intention. Navigation patterns with three search strategies are included to find the desired images. For each user's browsing behaviours, offline operation for knowledge discovery is triggered to perform navigation pattern mining. The main drawbacks of this system are image retrieval in global feature space and results depends only on the navigation pattern of users.

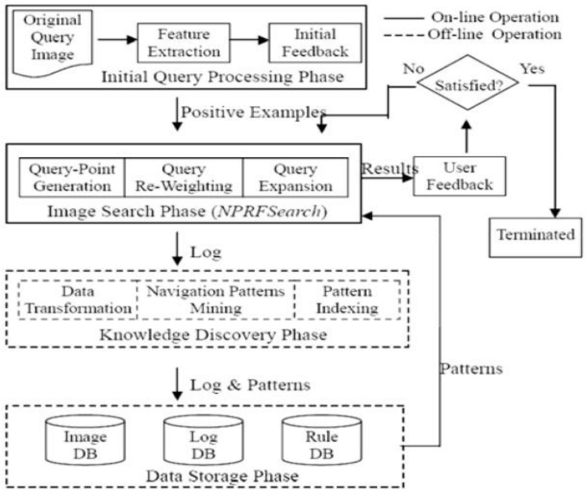

Figure 1: Workflow of NPRF Search [4]

In [5] Wei Bian and Dacheng Tao proposed a new dimensionality reduction algorithm for relevance feedback in the content based image retrieval is called Biased Discriminative Euclidean Embedding (BDEE). The samples in the original dimensional ambient space is transformed to low level visual features to discover intrinsic coordinates of an image. BDEE models both the interclass geometry and interclass discrimination of each image. It does not ignore the manifold structure of samples. BDEE is a subspace learning method in which mapping vector is used to map high dimensional space to low dimensional space.

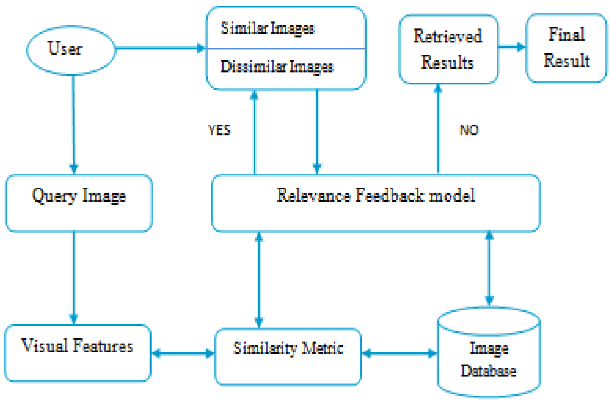

Figure 2: Architecture of CBIR system

In the process of BDEE technique distance between positive samples and negative samples should be large and distance between positive samples should be small. When a query image is given to the system, first low level visual features are extracted. Then all images in the database are sorted based on the Euclidean distance. If the user is not satisfied with the initial results then the Relevance Feedback process is started. The user labels some top query images as positive or negative samples. This RF model is trained and updated based on BDEE algorithms. The advantages are reduces under sampled problem, reduces computational complexity and maintain the manifold regularization structure. Also consider unlabeled samples for dimensionality reduction.

In [6] Yu-Chen Wang, Chin Chuan Han, Chen-Ta Hsieh, Ying-Nong Chen, and Kuo-Chin Fan proposed a Feature Line Embedding Biased Discriminant Analysis (FLE-BDA) for performance enhancement in relevance feedback scheme. It maximizing margin between relevant and irrelevant samples at local neighborhood so that relevant images and query image can be quite close, while irrelevant samples are far away from relevant samples. In this subspace learning method, find a linear transformation matrix from relevant or irrelevant images that is used in dimensionality reduction. The retrieval process includes 1) A query image is inputted to the IR system. After calculating the similarity values, gallery images are ranked. 2) Users label the relevant or irrelevant images according to their preference. 3) Then user's' feedback is adopted to find a new transformation. 4) The gallery images are re-ranked to obtain the retrieval results in the next round. Two labels are assigned to the top ranking images according to users' preference. Feedback with relevant or irrelevant labels represents users' preference. The within class scatter is calculated from the image samples with positive labels, while the between-class scatter is calculated from those with negative labels. Based on these assigned labels, the within class and between-class weighted graphs are constructed for maximizing the margin of relevant and irrelevant samples. Then new distance between query and images are calculated. The advantages are dimensionality reduction, solve singular problem in the high dimensional space, increases generalization and robustness using Laplacian regularization. The disadvantage are computational complexity is very high due to the large scale dataset.

In [7] Lining Zhang, Lipo Wang, and Weisi Lin [3] proposed an conjunctive patches subspace learning (CPSL) method for learning an effective semantic subspace by exploiting the user historical feedback log data with the current data. CPSL effectively integrate the discriminative information of labeled log images, geometry information of labeled log images and weakly similar information of unlabeled images. For creating a reliable subspace, need to build different kinds of local patches for each image. Apart from other Relevance Feedback techniques, Collaborative Image Retrieval system integrates regular online RF schemes with an offline feedback log data. From the figure, the CIR systems first collect RF information from user which can be stored in an RF log database. If user feedback log data is unavailable then the CIR system performs exactly like RF based CBIR system. If the user RF information is available, the algorithm can effectively exploit the user feedback log data. The image retrieval can be done in less iteration than regular RF schemes with the help of the user historical feedback log data. The advantages are there is no need for the explicit class label information for images in the dataset and also consider local information of each image. The disadvantage is increasing time complexity to take both user data and user feedback log data.

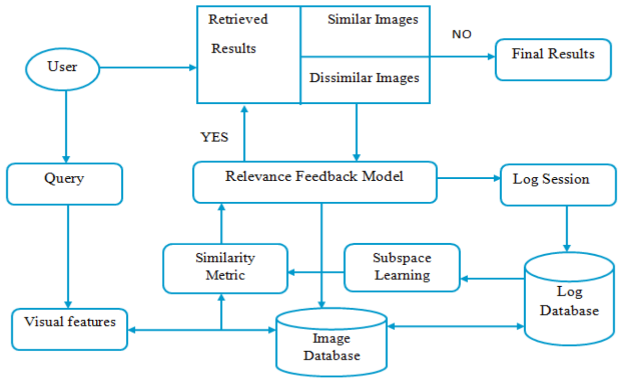

Figure 3: Architecture of Log Based CBIR System

In [8] Lining Zhang, Hubert P. H. Shum and Ling Shao proposed a discriminative semantic subspace analysis (DSSA) method to bridge the gap between low level visual features and high-level semantic concepts by exploiting the training images with pairwise constraints. This DSSA method effectively learn a reliable subspace from both labeled and unlabeled images with similar and dissimilar pairwise constraints without using any explicit class label information. DSSA integrates the local geometry of labeled similar images, the discriminative information between labeled similar and dissimilar images, and the local geometry of unlabeled images. First the low level visual features are first extracted then all images in the database are sorted based on a predefined similarity metric. The system requires user to label some semantically similar and dissimilar images as the positive and negative feedback samples, respectively. Using these labeled similar and dissimilar samples as the training data, RF model can be obtained based on certain machine learning techniques. The similarity metric can thus be updated together with the RF model. Then, all images are sorted based on the recalculated similarity metric. If the user is satisfied with the refined results, RF is no longer required and the system gives the final results, which are the most semantically similar images with the query image. Otherwise, RF is performed iteratively. The advantages of DSSA involve the local similar and dissimilar pairwise constraints of feedback samples and do not impose any label constraints on feedback samples. It effectively finds most discriminative subspace compared with classical supervised subspace analysis methods with explicit class label information. It never meets the problem of numerical computation.

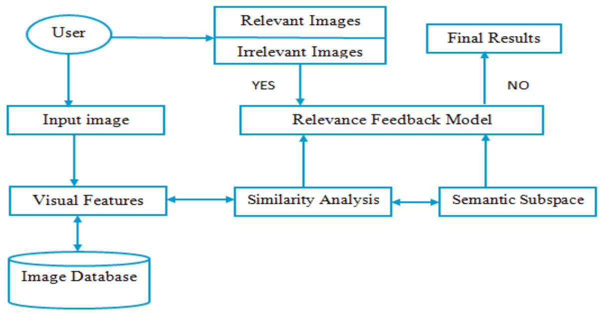

Figure 4: Framework of RF based CBIR system

3. CONCLUSIONS

Content based image retrieval is a technique to retrieve more relevant images. Retrieve similar images only is a standing problem in digital image processing. The performance of CBIR system is improved by introducing relevance feedback techniques in the system. Several feature modification and subspace learning based relevance feedback methods are studied. Various systems use feature modification of each image and tries to retrieve relevant images. But these systems do not suitable for high dimensional images. Several subspace learning relevance feedback methods provides more relevant images compared with feature modification based methods. It also considers local information of images and aims those similar images close to but dissimilar images are far away from query image. This paper focuses on the different relevance feedback techniques in digital image processing.

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