OPTIMIZING CONTENT BASED IMAGE RETRIEVAL IN P2P SYSTEMS

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Abstract

Content Based image retrieval (CBIR) is next big thing on search market. Performing content based image retrieval on internet databases connected using P2P network is the scope of our work. In case of unstructured P2P network CBIR has many challenges in terms of routing, match making etc. Authors in [1] have proposed a P2P-CBIR search engine to provide scalable image retrieval which can adaptively control the query scope and progressively define the accuracy of query results. But the problem in this solution is that query search time is high. We take this problem and propose optimizations to work in [1], so that the image search time can be reduced.

Keywords: *peer-to-peer networks; Multi-instance query; content based image retrieval; scalable retrieval; network search configuration.*

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1. INTRODUCTION

Advancement of digital media coding and Internet technology have enabled, Peer-to-Peer (P2P) networks to share files, transferring real-time video streams, and performing Content-Based Image Retrieval (CBIR) in recent decades. In the P2P networks, each connected peer serves simultaneously as a server and a client, which can distribute computation and network traffics to peers to provide efficient streaming and CBIR services.

The CBIR has been developed over the past decade since international image/video coding standards, such as JPEG, MPEG-4, H.264, and HEVC, have been widely used and distributed over Internet. The CBIR engine can help to find user interested relevant multimedia contents, either through multi-instance query or relevance feedback control. Before the CBIR search engine being developed, text information is the only precise data used to perform content similarity retrieval, such as filename, creator, and content descriptions.

However, the text-based CBIR requires human annotation and content categorization, such that large scale retrieval is not feasible. In addition, the categorization and annotations would be different through different human labeling, which would bias the retrieval results.

To perform server-client CBIR, the server has to record addresses and feature characteristics of all client peers. To respond a query, the server helps the query peer, P, to forward the query message, Q, to all peers with relevant contents, which would perform retrieval and transmit relevant images toward P. This centralized approach suffers heavy network traffics in that unnecessary retrieval and transmission are involved. To eliminate the centralized traffic loading, P2P CBIR is proposed.

Multi-instance query is widely used by the CBIR search engine to improve retrieval accuracy and reduce retrieval processing time. As one image would demonstrate various types of features, performing multi-instance query with multiple feature (MIMF) types can yield more accurate and robust retrieval results, which can be achieved by assigning weighting to different similarity ranks corresponding to different feature types. Authors in [1] proposed to perform MIMF on the P2P paradigm for progressive and scalable retrieval. In this method, the query search time was high because of the network delay and image matching at each peer. We take this problem as our motivation and propose methods to optimize the query search time.

2. RELATED WORK

The MPEG-7 standard provides normative descriptors, such as color, texture, region, and shape descriptors, for effective visual data retrieval [2]. These descriptors represent visual contents with numerical feature values from which the similarity could be measured quantitatively. They provide a numerical measurement space for image knowledge discovery and data mining (KDD). In general, one CBIR search engine provides the relevance feedback function to recognize user's definition on image similarity. In addition, utilizing multiple feature types would help the search engine to increase the retrieval accuracy and reduce the network traffic in the P2PCBIR system.

Previous works, such as IBM's Query by Image Content (QBIC) [3], Blobworld [4], and visualSEEk [5], proposed to extract low-level features from locally segmented image regions. For the QBIC system, the objects or regions in images are segmented and labeled manually. In terms of feature description, the color, texture, and shape features could be extracted from the objects, regions, or the whole image. The Blobworld proposed to segment an image into a set of region that are coherent in color and texture features. The similarity between the query image and the one in the image database is computed through the similarity regions matching. The VisualSEEk extracts the color and texture features from the salient regions segmented in the images, and further takes the geometric properties of regions (e.g., size, absolute, and relative spatial locations) into considerations.

PicToSeek [6] is an object based retrieval system, in which the invariants of color and shape features for the object in each image are evaluated based on the criteria: illumination conditions, viewpoint invariance, and geometry properties of the object.

However, how to justify segmentation results become critical in terms of image segmentation techniques. In addition, the problem of computing a similar region pair set with the maximum covered area is NP-hard [7].

Several researches were conducted to study the multi-instance learning measure to select the semantic regions from query images automatically [8][9]. The selected regions from query images are labeled as common positive from users' relevance feedback.

Some researches proposed to extract global or local features from images to perform image classification and image/video retrieval [13]-[16]. The Scale Invariant Feature Transform (SIFT) [17][18] is a widely used local feature descriptor that extracts distinctive invariant key points from local patches in images. According to the clustering procedure, each patch described by the feature key point is categorized into the set corresponding to specific words. Therefore, a bag of-words (BOW) [19][20] is built as the feature vector to describe the visual content of one image.

Speeded Up Robust Features (SURF) [21] descriptor approximates the second order Gaussian derivatives in Hessian matrix, and exploits integral images to extract the local feature points. Principal Component Analysis (PCA)-SIFT [22] projects the normalized gradient image vector to a compact feature vector. Since SURF and PCA-SIFT descriptors demonstrate lower dimensional feature vectors [23], they spend less time for matching between two images, as compared to the SIFT descriptor. In contrast, global features can be extracted from images such as color correlogram and Tamura texture descriptors. The color correlogram [24] presents the spatial correlation between pairs of pixels' colors with distance. As compared to the color histogram, color correlogram is more robust to different image processing procedures, including spatial translation, different view of the same scene, and large changes in appearance. Tamura texture descriptors [25] extract six basic texture features corresponding to human visual perception: coarseness, contrast, directionality, line-likeness, regularity, and roughness.

Experiments suggest that the first three texture features, i.e., coarseness, contrast, and directionality, are efficiently in images classification and segmentation.

3. PROBLEM STATEMENT

The P2P-CBIR system diagram proposed in [1] is demonstrated in Fig. 1, which comprises off- and on-line stages.

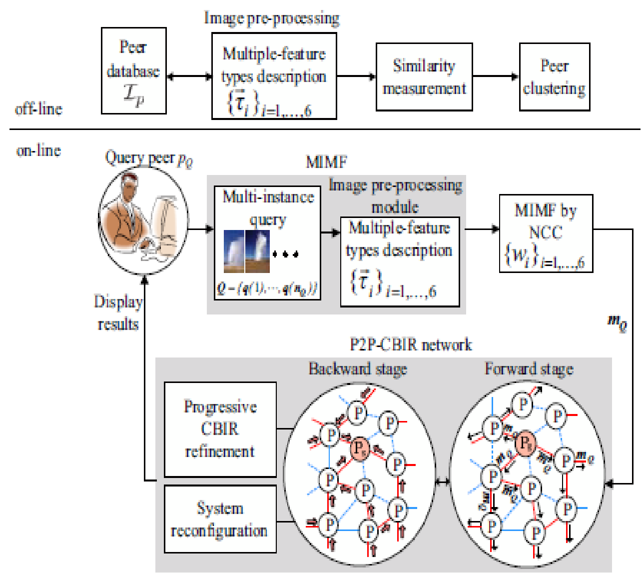


Fig. 1: The P2P-CBIR system diagram.

At the off-line stage, an image pre-processing module was integrated in each peer to extract descriptors of new images, such as color, texture, and shape. At the on-line stage, the query peer P that received the Q performs MIMF.

The problem in this approach is that the query feature is matched against each image in the peer during the online search stage. This results in bigger search time.

4. PROPOSED SOLUTION

We introduce two additional concepts in offline phase of P2P-CBIR which will help to achieve reduced search time.
1. Clustering of Peers
2. Constructing search index for Peer cluster

In the online phase, the way of searching is modified to achieve fast search time.

4.1 Clustering of Peers

Peers must be grouped together based on any parameters like peers in a particular geographical area. Each peer will advertise the number of requests it has received till recent to all the neighbors in its geographical area with a distance of K hops. Once all the peers have exchanged the information, the peer node with maximum number of request till now will become the cluster head. All the other peers will come the part of the cluster. A peer node can also be part of two clusters. This occurs for the case of boarder peers. The cluster head peer will start a mobile agent. This mobile agent will visit all the peers in the cluster and visit the cluster head. The mobile agent will carry information of the image feature cluster information in each peer to the cluster head peer.

4.2 Constructing Search Index for Peer Cluster

The mobile agent will bring the feature vector of images in each peer to the cluster head peer. Based in this clustering is again done to group the image features. The mobile agent cannot bring the all image feature information from other peers at one shot. So the clustering algorithm which we will implement must be a agglomerative clustering algorithm. With this cluster information, a search index must be constructed. The search index will maintain the map of what features are available at the peer cluster as the whole and the whereabouts of each features in the peer cluster.

4.3 Modified Search

In the search phase, when the query is sent over P2P network, each peer will forward the query to its cluster head peer. Once the cluster head peer receives the query, it will search in the search index and look for the presence of the target feature presence or similarity with any features in its search index. If any matching entry is found the query is redirected to the peers in which feature is found. If the no matching entry is found, the cluster head will forward to neighbor cluster head.

5. ADVANTAGES OF OUR SOLUTION

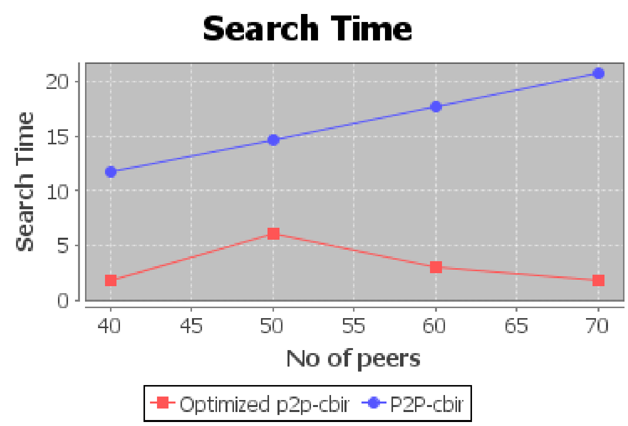
With the search index constructed and kept at peer cluster head node, the search on each peer for the match is avoided. This way the search time is shortened. With the bigger cluster size, the search time can be reduced drastically.

6. PERFORMANCE ANALYSIS

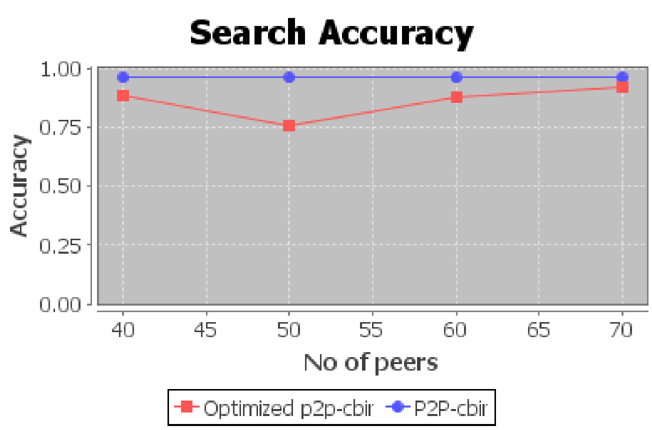
The databases comprise 500 images, some of which are collected from Corel image database and Caltech 101, and the others are collected from professional websites. Each peer is distributed 15 images randomly different categories. For peer clustering, each peer records three random links and two attractive links for CH, SCD, CSD, CLD, EHD and DWT features, respectively.

We measured two parameters accuracy of match and the search time. Our main objective in this paper work is to reduce the search time without affecting the accuracy in a bigger way.

We compared our proposed solution to the solution proposed in [1].



From the performance result, we see that the search time is less than the P2P-cbir system proposed in [1]. The reason for this reduction is because of the peer search index maintained in the cluster head. Due to this, we have shortened the search area and it reflects in reduction in search time.



The accuracy is comparatively lesser in our approach during initial stages, but improves with number of nodes because of more results returned to the user.

7. CONCLUSIONS AND FUTURE WORK

We have detailed our proposed solution for reducing the search time for CBIR in P2P-CBIR system. In future we plan to analyze the performance of our solution in terms of search time for different cluster sizes and compare with existing solution. In addition we also plan to propose a representation of search index to enable faster search using spare coding representations.

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