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Multi Query Content Based Image Retrieval System Based on Pattern Mining

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Abstract—Abstract - As the digital image collections are growing at more rapid rate, need for efficient and effective tools for retrieval of query images from the database has increased very significantly. In this paper a new method for object specific content based image retrieval using multiple query images is proposed. Usage of multiple query images helps in obtaining different description of the centric object of the query images like when same object is captured at different angles, distance or viewing conditions. This helps in obtaining a very diverse and precise retrieval results. A novel method based on pattern mining with minimal description length principle is proposed to derive the very suitable set of patterns to describe the centric query object from the set of scale and rotation invariant local features in the query images. This produces a strong object-specific mid-level representation of the query image. The image database can be searched efficiently and similar images can be retrieved based on this representation.

Keywords- Content based image retrieval (CBIR), Feature matching, Multiple query image retrieval (MQIR), semantic gap reduction techniques, pattern mining

I. INTRODUCTION

The advancement in digital image capturing and producing techniques has rapidly increased the usage of digital images in almost all the fields. Easy access to cameras and mobile phones with built in camera at affordable cost also has increased the count of digital images in great rate at very short time period. A comparison of real-time data from the US Census Bureau and GSMA intelligence a mobile network analysis firm reveals that the number of active mobile devices exceeded the number of humans. That is number of active mobile devices presently stands around 7.25 billion. Worldwide image capture forecast by InfoTrend in 2015 believes that consumers will take 1 trillion photos worldwide in 2016 and the number will increase to 1.3 trillion photos by 2017. The increased use of internet and social media has added up to the amassment of large amount of digital images in the web. Mary Meeker's annual Internet Trends report [1] says that Internet users have uploaded an average of 1.8 billion digital images every day. That counts to 657 billion photos per year.

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When a large number of images are stored in the database it is not easy to annotate every single image manually for grouping wise retrieval and processing. Hence, content based image retrieval methods are used, so that the matching images are retrieved based on the visual subjects of the query images such as colour, points, textures or any such information that can be automatically gathered from the images. The retrieved images are further ranked in accordance to the relevance among the query image and images in the database based on a similarity measure which can be calculated from the extracted features. Hence the efficiency of a CBIR system highly depends on the effectiveness with which the lower level features extracted from the image represent the higher level semantics of the image. The usage of multiple query images is proposed to reduce the semantic gap rather than the conventional single query approach.

II. CBIR SYSTEMS

Content-based retrieval utilizes the contents of images to represent as well as access the images from a large database. Content-based retrieval system can be divided into two types: off-line process of feature extraction and online process of image retrieval. Figure.1. shows the architecture of content-based image retrieval.

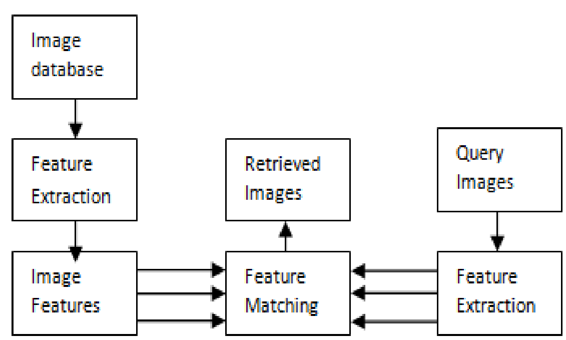

Fig.1: Architecture of CBIR system

In off-line stage, the system extracts visual attributes like colour, shape and texture of each image in the database based on the pixel values and stores them in feature vector database. The feature data also known as image features for every visual attributes of each image is very smaller in size compared to the original image data, thus the feature database contains a compact form of the images in the image database. Using feature vector representation of image database over the original pixel values significant compression can be achieved. In on-line image retrieval, the user submits a query image to the CBIR system in search of desired images. The query image is represented with a feature vector in this system. The similarities among the feature vectors of the query example and those of the images in the feature database are later computed and ranked. Retrieval is computed by applying an indexing scheme which provides an efficient way for searching the image database. Finally, the retrieval results are ranked by the system and then the system returns the images which are most similar to the query images.

In the matching process, the system compares the image signature of query image with the image signatures of the other images stored in the database. For matching, the distance between image signatures of the query example and database images is computed and then the images are ranked according to their distance threshold. Typically Euclidean distance is considered as the most important measure. Then according to ranking, system returns the results that have visual similarity to the query. Feature matching can be done in two ways. One way is by region in which regions can be obtained by segmentation and then distance between two regions is measured based on their low level features. Other is by image which consists of number of regions. The Euclidean distance between point p and point q is the length of the line segment connecting those points. In the Cartesian coordinates, If p = ($p_1, p_2,..., p_n$) and q = ($q_1, q_2,..., q_n$) are two points in the Euclidean n-space, then distance (d) from p to q, or from q to p is given by the Pythagorean formula:

$$d(p,q) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2} \quad (1)$$

$$= \sqrt{\textstyle\sum_{i=1}^{n}(q_i - p_i} \quad (2)$$

In recent years several other distance measures have been developed for histograms like city block distance and the Minkowsky distance.

III. Semantic Gap In Cbir And Reduction Techniques

Although great interest and a large number of new techniques and systems are emerged in content-based image retrieval in the last decades, the gap between low-level visual features and high-level semantic understanding of images, which is also known as the semantic gap problem exists.

The gap between the object in the world and the information in a computational description derived from a recording of that scene is the bottleneck to further improvement of the performance of a content-based image retrieval system. Therefore, in order to solve the problems and improve CBIR performance, Region Based Image Retrieval approaches, image annotation, and relevance feedback [3] have been received more attention in the recently years.

A. Image Annotation

The problem of narrowing semantic gap lies in estimating the context of the search requests or the usage contexts for retrieved images. For example, in content based approaches a user query (usually in the form of a sample images), is matched against low-level features (e.g. colors, shapes), extracted from the image, thereby providing no insight into why the user wants to retrieve the specified image or of how the retrieved image will actually be used [4]. In order to show image semantics at a higher level, one of the approaches uses different models and machine learning methods to identify the relation between image visual features and semantics, then label the image with keywords, this is image annotation.

Most existing image annotation approaches can be classified into two categories, probabilistic modeling based methods and classification based methods. Classification based methods treat keywords as classes and trained classifiers are employed to annotate an input image based on classification results. Probabilistic modeling based methods attempt to obtain the correlations or joint probabilities between images and annotations. The disadvantage in this approach is that it requires large amount of human labor in the manual annotation when the image collection is very large. It is hard to precisely annotate the very rich content of an image by humans due to the perception subjectivity.

B. Region-based Image Retrieval

RBIR is an image retrieval approach which concentrates on contents from regions of images and not the content from the entire image as in early CBIR [5]. For RBIR, it first segments the images into a number of regions, and extracts a set of features, which are identified as local features, from segmented regions. A similarity or the distance measure determining the similarity between the target regions in a query and a set of segmented regions from other images is utilized later to determine relevant images to the query based on local and regional features. The motivation of RBIR approaches are based on the fact that a high-level semantic understanding of the images can be better reflected by local features of images, rather than global features. Since users are often more concerned with interested objects in images when using an image retrieval system, considering images based on region (RBIR) allow users to pay more attention to regional properties that may a better characterize objects that are also made up of local regions. This strategy is able to better reflect the characteristics of images from the perspective of image region and objects, and in turn further improve the image retrieval performance. One of the drawbacks of such systems is that it is difficult to determine the significance of different regions. Also they are computationally costly and time consuming. These systems also require efficient region matching algorithm to effectively find the similarity between images.

C. Relevance Feedback

Relevance feedback (RF) is a method where interactive supervised learning technique has been used to bridge the semantic gap between the low-level features of the image and the semantic content of the images and, thus, to improve the retrieval results. In specific, RF attempts to insert a subjective human perception of image similarity into a CBIR system and hence for this to be accomplished, the users are required to assess, in each RF round, the retrieved images as relevant or the image as irrelevant to the initial query and to submit their assessment as a feedback to the system. Then, the system takes into account of their feedback and updates in the appropriate way the image ranking criterion. Here speed of the performance is the major drawback. Satisfactory results can be achieved only after several iterations. Often a single image used as query may not be able to reflect what the user has in mind and hence many not able to retrieve relevant images according to the user's requirement, widening the semantic gap. Multi-query approaches have been proposed to overcome limitations of traditional CBIR systems to improve the retrieval efficiency and reduce the semantic gap. Various studies show multi query approaches provides better precision value than the traditional single query CBIR.

IV. MULTI-QUERY CBIR SYSTEMS

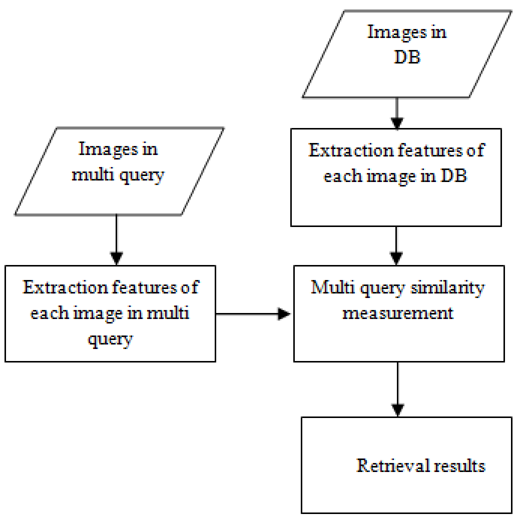

Fig.2 Architecture of Multi-Query CBIR system

Figure 2 presents a general Multi-Query Image Retrieval (MQIR) system which is implemented in the CBIR. The features of every single image in the database are stored in the index table. The MQIR system extracts features of images in multi-query. Every image in the query set has its own representations for the query processing. For each query image in multi-query, the proper weight for similarity measurement is set. And finally, the MQIR system will express the retrieval results in similarity ranking order.

V.RELATED WORK

Elena Stojanova et al (2013) [6] proposed maximum of the multiple queries approach where each query is executed separately and separately from the other queries in the same set. When the retrieval phase is finished, the retrieved ranked lists are combined so that the rank of every image in the database is determined as the maximum of the individual scores extracted from each query. In average of multiple queries method rather than calculating the maximum of each score, the image score in final ranked list is calculated as the average of the individual scores. The drawback of this approach is that the bigger number of images in the query set not always leads to better results. Yanzhi Chen et al (2012) [7] proposed a multi-group method to improve the content based image retrieval performance using multi-query. Query instances are used to automatically collect the set of query-dependent positive and negative data samples as used by discriminative query expansion (DQE). In contrast to average query expansion (AQE), which uses positive samples to improve query recall, the dataset images is re ranked in DQE by a data-dependent weight vector learnt from both positive and negative samples. The disadvantage of this method is the requirement of negative images, which may not be available in all the cases. Basura Fernando (2013) [8] proposed a new method based on pattern mining in the multiple query CBIR systems. Using the minimal description length principle, the most suitable set of patterns is derived to describe the query object from the set of query images, with patterns corresponding to local feature configurations. Though it is a very complex technique, this results in a powerful object-oriented mid-level image representation. The archive dataset can be obtained even without costly re-ranking based on geometric verification. Fatih Calisir (2015) [10] proposed an approach to improve the mobile image retrieval performance using multiple query images. Here bag-of-visual-words approach is used to represent the images, and employ early and late fusion strategies to utilize the information in multiple query images. The major drawbacks of the above methods is that they are more suitable only for single semantic multiple query images. They cannot support query images with different semantics, where features of every query image is required to be present in the retrieved images. Considering the content-based image retrieval problem for multiple query images corresponding to different image semantics, Ko-Jen Hsiao (2015) [11] propose a novel multiple-query information retrieval algorithm that combines the Pareto front method with efficient manifold ranking. The goal is to find images related to all queries. This algorithm can retrieve samples that are not easily retrieved by other multiple-query retrieval algorithms. Drawback of this method is that it is hard to incorporate the entire features of every image and may discard some important features in a particular image. Vimina E R (2015) [12] proposed a multi query system using query replacement algorithm which utilizes the statistical features of a query image set to determine the similarity of the candidate images in the database for ranking and retrieval. In this work a novel query replacement algorithm is proposed for boosting the efficiency of a multi-query CBIR system. The algorithm is based on the principle that if an element in set X is to be replaced with an element in set Y, it will cause minimum information change if the replaced element has high similarity with the element being replaced. Using this method with smaller number of query images, high retrieval precision rate can be obtained but the major drawback is high computation cost during the run time.

VI. PROPOSED APPROACH

A. Feature extraction

For any image, interesting points on the image can be extracted to provide a feature description of the image. This description is extracted from a query image and later can be used to identify the similar images from the set of images from the database. To perform a reliable recognition, it is very important that the features extracted from the query image be detectable even when there is changes in image scale, noise and as well as illumination. Here SIFT descriptor [19] can be used to extract features.

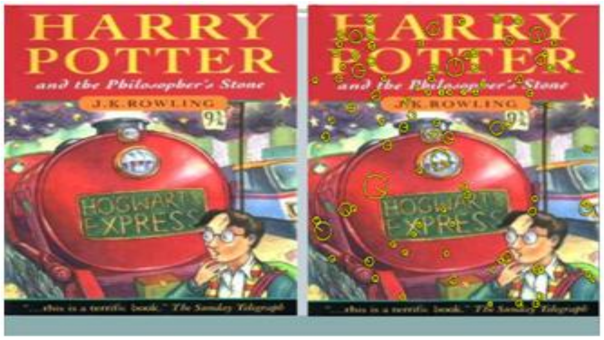

Fig.3 SIFT key points identification

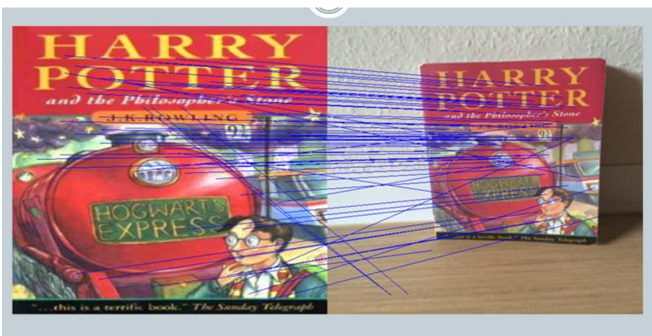

Fig.4 Matching of SIFT features for two image

B. *Pattern mining*

Frequent Item set Mining (FIM) [13] is the most popularly used pattern mining technique, only discovers patterns that are frequent (as often used in computer vision [14, 15, 16]. With FIM, all closed frequent patterns are used to represent the query object. As a result, a large number of selected patterns describe the same parts of the object and hence they are redundant. This model overly represents the data and, consequently, represents the noise too. Hence FIM is not the most suitable approach for the image retrieval. Instead, what a model that best explains the query image data (i.e., the query object) without redundancy is needed. Either KRIMP algorithm [17] or SLIM algorithm [18] can be used to obtain such solution. They use the minimal description length (MDL) principle to discover a set of patterns that together best explain the data.

C. *Matching and Ranking*

The overall process can be classified into offline process and online process. In the offline process the images which are stored in the database are indexed. Features of the images are extracted and stored according to the corresponding image index values. In the online process the query images are obtained. Features of the query images are extracted. Each query image produces number of features. Patterns of features repeated in the query images are identified. The numbers of patterns are reduced based on the minimum description length principle. The patterns of features are matched with the features of the images stored in the database. The images stored in the database are ranked based on the number of patterns matched and the top N images are retrieved.

VII. RESULTS AND DISCUSSIONS

A. *Single query image*

When single query image is given, SIFT features are extracted from the image and based on the matches of the number of SIFT features the images in the database are ranked and the top images are displayed.

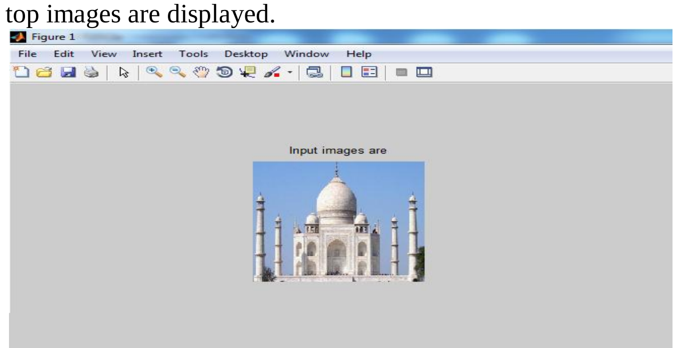

Fig.5 Query image for CBIR.

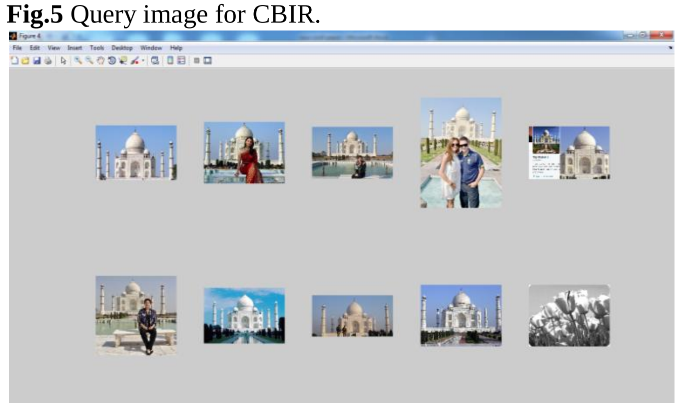

Fig.6 CBIR for single query image

B. *Multi Query images*

When multiple query image are given, SIFT features are extracted for each image and patterns are extracted. Based on the number of patterns present the images in the database are ranked and the top images are displayed. The experiment shows that when multiple query images are used the retrieval results are with higher precision rate than the single query approach. When the number of query images is increased, the precision rate also gets increased proportionally.

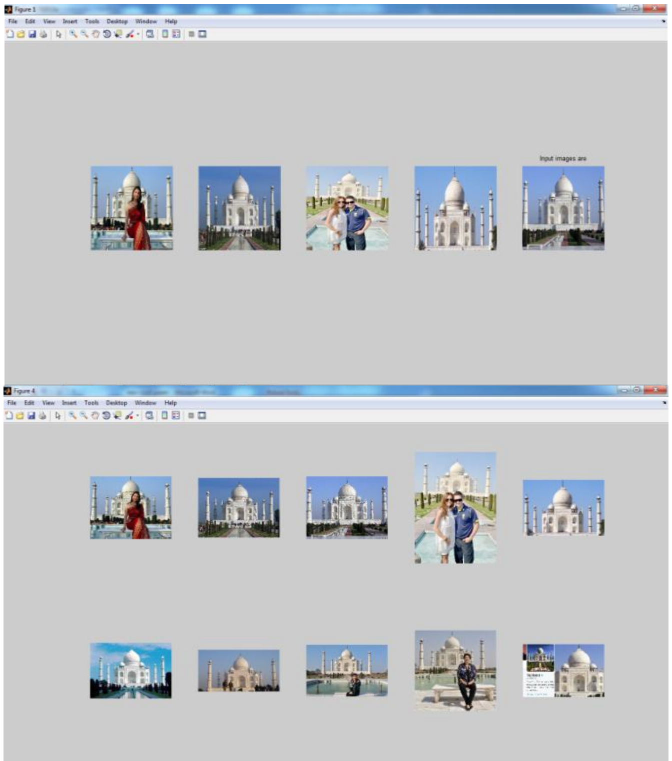

Fig.7 CBIR for multiple query images

C. Performance

The performance is measured in terms of precision. The precision is given by the total number of relevant images retrieved among all the retrieved images.

$$precision = \frac{Relevant\ Images\ Retrieved}{Total\ Number\ of\ Images\ Retrieved} \quad (3)$$

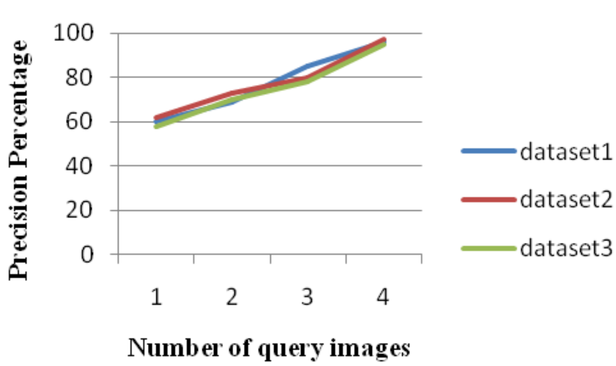

Fig.8 Performance graph

VIII.CONCLUSION

In this paper, essential concepts of single-query content-based image retrieval systems are studied and limitations of various traditional semantic gap reduction techniques for CBIR are examined. Multi-query approach is proposed for efficient semantic gap reduction in CBIR. Survey is done on different multi-query content based image retrieval systems. Techniques used in these systems increases the efficiency of content based image retrieval systems by reducing the spatial gap between low level features and high level concepts and thus increases the precision rate of image retrieval. Experimental results shows that usage of SIFT feature descriptor for feature extraction produces better results than other feature extraction algorithms. The proposed multi query image retrieval based on pattern mining approach produces higher precision rate.

REFERENCES

[1] Mary Meeker, “Internet trends”, KPCB Code conference, 2015.
[2] A. Smeulders, M. Worring, S. Santini, A. Gupta and R. Jain, “Content-based image retrieval at the end of the early years”, IEEE Transactions on Pattern Analysis and Machine Intelligence 22 1349–1380, 2000.
[3] Feng H. Ren, “Multi-image query content-based image retrieval”, University of Wollongong thesis collections, 2006.
[4] Dimitri A. Lisin, Marwan A. Mattar, Matthew B. Blaschko, “Combining local and global image features for object class recognition”, 2010.
[5] Niket Amoda and Ramesh K Kulkarni, “Efficient image retrieval using region based image retrieval”, Signal & Image Processing: An international journal, Vol.4, No.3, June 2013.
[6] Elena Stojanova, Katarina Trojacanec, Ivica Dimitrovski and Suzana Loshkovska, “Multi-query content based medical image retrieval”, The 10th conference for Informatics and Information Technology, 2013.
[7] Yanzhi Chen, Xi Li, Anthony Dick and Anton Van den Hengel “Boosting object retrieval with group queries” IEEE Signal Processing Letters, Vol. 19, No. 11, November 2012.
[8] Cai-Zhi Zhu, Yu-Hui Huang and Shin’ichi Satoh, “Multi-image aggregation for better visual object retrieval” IEEE International conference on acoustic, speech and signal processing, 2014.
[9] Fatih calisir, Muhammet Bastan, Ugur Gudukbay and Ozgur Ulusoy, “Mobile image search using multi-query images”, IEEE conference on signal processing and communication application, 2015.
[10] Basura Fernando and Tinne Tuytelaars, “Mining multiple queries for image retrieval: On-the-fly learning of an object-specific mid-level representation”, IEEE International conference on computer vision, 2013.
[11] Ko-Jen Hsiao, Jeff Calder and Alfred O. Hero, “Pareto-Depth for Multiple-Query Image Retrieval”, IEEE Transactions on image processing, Vol. 24, No. 2, February 2015.
[12] Vimina E R, Ramakrishnan K, Navya Nandakumar and Poulose Jacob K, “An efficient multi query system for content based image retrieval using query replacement”,16th IEEE conference on Software engineering, artificial intelligence, networking and parallel/distributed computing, 2015.
[13] R. Agrawal and R. Srikant. “Fast algorithms for mining association rules in large databases”. In VLDB, 1994.
[14] A. Gilbert, J. Illingworth, and R. Bowden. “Fast realistic multi-action recognition using mined dense spatio-temporal features”. In ICCV, 2009.
[15] T. Quack, V. Ferrari, B. Leibe, and L. Van Gool. “Efficient mining of frequent and distinctive feature configurations”. In ICCV, 2007.
[16] B. Yao and L. Fei-Fei. Grouplet: “A structured image representation for recognizing human and object interactions”. In CVPR, 2010.
[17] J. Vreeken, M. Leeuwen, and A. Siebes. “Krimp: mining itemsets that compress.” Data Min. Knowl. Discov., 23:169–214, 2011.
[18] Smets, K. and Vreeken, J. “Slim: Directly Mining Descriptive Patterns”. SIAM SDM, 2012.
[19] David G. Lowe, “Distinctive Image Features from Scale-Invariant Keypoints”, International Journal of Computer Vision, 2004