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A Survey on Image Retrival Using Query Based Approach to Feature Extraction

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ABSTRACT: Extensive digitization of images, paintings, diagrams and explosion of World Wide Web (www), has made traditional keyword based search for image, an inefficient method for retrieval of required image data. Content-Based Image Retrieval (CBIR) system retrieves the similar images from a large database for a given input query image. To search for images, a user may provide query terms such as keyword, image file/link, or click on some image, and the system will return images "similar" to the query. The similarity used for search criteria could be meta tags, color distribution in images, region/shape attributes, etc. Image meta search - search of images based on associated metadata such as keywords, text, etc. Content based image retrieval (CBIR) – the application of computer vision to the image retrieval. CBIR aims at avoiding the use of textual descriptions and instead retrieves images based on similarities in their contents (textures, colors, shapes etc.) to a user-supplied query image or user-specified image features.

Keywords: CBIR, survey, tag based, feature computation, system modelling.

I. INTRODUCTION

The importance of digital image databases depends on how friendly and accurately users can retrieve images of interest. Therefore, advanced search and retrieval tools have been perceived as an urgent need for various image retrieval applications. The earliest search engines have adopted textbased image retrieval approaches. These solutions have shown drastic limitations because digital images to be mined are either not labelled or annotated using inaccurate keywords. In other words, text-based retrieval approaches necessitate manual annotation of the whole image collections. However, this tedious manual task is not feasible for large image databases.

Content Based Image Retrieval (CBIR) [1] is a scheme that searches images from a large database by means of visual contents, as per the interest of user. Since 1990s, it has been rapid growing research area. Moreover, in the past years, the researchers have made notable results. In late 1970s, the field got its foundation in a conference on Database Technical for Pictorial Applications which was held in Florence [3]. This made the researchers to be attracted towards the field. At early stage, the technique was based on textual annotations of images i.e. images were first annotated with text and then searched using a text-based scheme from typical database systems [2]. This scheme was little simple and could sometimes fail to deliver precise results. Moreover, it is not easy to automatically generate annotations for each image, therefore manual annotation was followed which is a clumsy and complicated task plus much expensive if we have bulk databases. Further in early 1990s, with rapid growth in internet and digital image sensors, usage and production of images increased which further created a need of CBIR systems. Since then, research on content-based image retrieval has developed rapidly [4].

A key component of the Content Based Image Retrieval system is feature extraction. A feature is a characteristic that can capture a certain visual property of an image either globally for the whole image, or locally for objects or regions. Some key issues related to CBIR systems are the following. First, how the extracted features can present image contents. Second, how to determine the similarity between images based on their extracted features. One technique for these issues is using a vector model. This model represents an image as a vector of features and the difference between two images is measured via the distance between their feature vectors.

There exist two approaches to search, to browse, and to retrieve images. The first one is based on textual information attributed to the images manually by a human. This is called concept-based or text-based image indexing. A human describes the images according to the image content, the caption, or the background information. However, the representation of an image with text requires significant effort and can be expensive, tedious, time consuming, subjective, incomplete, and inconsistent. To overcome the limitations of the text-based approach, the second approach, Content-Based Image Retrieval (CBIR) techniques are used. In a CBIR system, images are automatically indexed by summarizing their visual features such as color, texture, and shape. These features are automatically extracted from the images.

In this paper, we introduce a method for performing clustering and feature selection simultaneously using the expectation-maximization (EM) algorithm [3]. We apply this method to a CBIR domain in which we have partial class information – for each image we know the "major" class, but images within each class can vary widely with respect to visual similarity. Our "customized-queries" approach (CQA) to indexing and retrieval in such domains was introduced in an earlier paper [4]. The approach first classifies a query using the features that best differentiate the major classes and then customizes the query to that class by using the features that best distinguish the images within the chosen major class. This approach was motivated by the observation that the features that are most effective in discriminating among images from different classes may not be the most effective for retrieval of visually similar images within a class. This occurs for domains in which not all pairs of images within a given class have equivalent visual similarity. For example in the domain of transportation classification, the features that best distinguish airplanes from cars differ from the features that best distinguish commercial jets and stealth fighters. Such domains are appropriate candidates for our approach.

This article lists out some essential works and contributions place in the direction of CBIR and presents a brief survey about different techniques. In addition of that the work is extended and obtained a new image retrieval model. The detailed discussion of the image retrieval model is given in further sections.

II. RELATED WORK

K. Stevenson and C. Leung (July 2005) proposed text-oriented document searching are relatively mature on the Internet, image searching, which requires much more than text matching, significantly lags behind. We find that current technology is only able to deliver an average precision of around 42% and an average recall of around 12%, while the best performers are capable of producing over 70% for precision and around 27% for recall.

A. Bhattacharya and A.K. Singh (Nov 2005) given a large collection of medical images of several conditions and treatments. We propose to automatically develop a visual vocabulary by breaking images into n × n tiles and deriving key tiles ("ViVos") for each image and condition. We experiment with numerous domain-independent ways of extracting features from tiles (color histograms, textures, etc.), and several ways of choosing characteristic tiles (PCA, ICA).

J. Li and J. Wang (2006) developing effective methods for automated annotation of digital pictures continues to challenge computer scientists. These new techniques serve as the basis for the automatic linguistic indexing of pictures - real time (ALIPR) system of fully automatic and high-speed annotation for online pictures. In particular, the D2-clustering method, in the same spirit as K-Means for vectors, is developed to group objects represented by bags of weighted vectors.

D.M. Blei and A.Y. Ng, and M.I. Jordan (2003) understanding how topics within a document evolve over its structure is an interesting and important problem. In this paper, we address this problem by presenting a novel variant of Latent Dirichlet Allocation (LDA): Sequential LDA (SeqLDA). This variant directly considers the underlying sequential structure, i.e., a document consists of multiple segments (e.g., chapters, paragraphs), each of which is correlated to its previous and subsequent segments.

Z. Guo, S. Zhu, Y. Chi, Z. Zhang, and Y. Gong (2009) proposed document similarity measures are required for a variety of data organization and retrieval tasks including document clustering, document link detection, and query-by-example document retrieval. In this paper we examine existing and novel document similarity measures for use with spoken document collections processed with automatic speech recognition (ASR) technology.

Konstantinos A. Raftopoulos (Feb 2013) proposed Markovian Semantic Indexing (MSI), is presented in the context of an online image retrieval system. Assuming such a system, the users' queries are used to construct an Aggregate Markov Chain (AMC) through which the relevance between the keywords seen by the system is defined. The users' queries are also used to automatically annotate the images. A stochastic distance between images, based on their annotation and the keyword relevance captured in the AMC is then introduced.

Forming a hierarchy of features for retrieval and storage has been explored by other researchers, but their end goals for doing so differ from ours. For example in the Four Eyes system [10], highly structured objects in images, such as buildings and trees, are represented hierarchically to facilitate structural comparisons with a query image. In "Texture features and learning similarity" by Ma and Manjunath [9], they used a hybrid neural network algorithm to learn similarity by clustering in the texture feature space and then fine tuning the clusters using supervised learning. Their approach builds a hybrid neural network classifier that is applied during retrieval to classify the query as one of the given classes. Then they select the nmost similar images within that class cluster using Euclidean distance. Note that

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the same feature set is used both for classification and for retrieval after classification. Our approach differs in that we do not require the feature sets for classification and retrieval to be the same.

Chen and Bouman [2] developed an approach that organizes images in "similarity pyramids" by grouping images with the closest distances, as defined by an L1norm distance metric, together. They used an agglomerative (bottom-up) clustering algorithmto build the pyramid. The resulting organization is used for indexing and browsing purposes. In contrast, we group images according to disease classes and subclasses in order to emulate how expert radiologists would categorize them. Furthermore, we use different feature sets for comparing similarity at each level and for each class. Chen and Bouman's approach used the same feature set and similarity metric throughout the organization of their hierarchy or "pyramid".

III. QUERY CLUSTERING

Query clustering is a technique for discovering similar queries on a search engine. Also it is a class of techniques aiming at grouping users' semantically related, not syntactically related, and queries in a query repository, and accumulated with the interactions between users and the system. Query clustering algorithm choosing an appropriate clustering algorithm is also very critical to the effectiveness and efficiency of the query clustering process. While choosing the clustering algorithm, the following things must be kept in mind:

- The algorithm should be capable of handling a large data set within reasonable time and space constrained.
- The algorithm should be easily extended to cluster new queries incrementally.
- The algorithm should not require manual setting of the resulting form of the clusters.

3.1 Agglomerative Method

Agglomerative method works by grouping the data one by one on the basis of the nearest distance measure of all the pair wise distance between the data point. Again distance between the data point is recalculated but which distance to consider when the groups has been formed. Single linkage, complete linkage, average linkage and centroid distance between two points, grouping the data until one cluster is remaining.

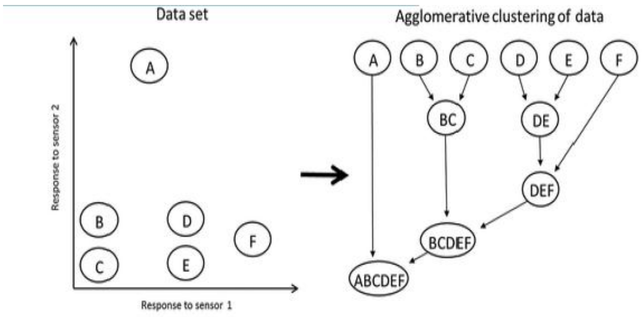

Fig.1. Agglomerative Clustering

Algorithm:

Agglomerative clustering Agglomerative clustering is starting out with *n* cluster for *n* data points, that is, each cluster consisting of a single data points.

Input: Number of cluster.

Output: One line per cluster which contains the points belonging to that cluster.

Method:

Step-1 Begin with the disjoint clustering having level L(0) = 0 and sequence number m = 0.

Step-2 Find the least distance pair of clusters in the current clustering, say pair (r), (s), according to d[(r),(s)] = min d[(i),(j)] where the minimum is over all pairs of clusters in the current clustering.

Step-3 Increment the sequence number: m = m +1.Merge clusters (r) and (s) into a single cluster to form the next clustering m. Set the level of this clustering to L(m) = d[(r),(s)].

Step-4 Update the distance matrix, D, by deleting the rows and columns corresponding to clusters (r) and (s) and adding a row and column corresponding to the newly formed cluster. The distance between the new cluster, denoted (r, s) and old cluster (k) is defined in this way: d [(k), (r, s)] = min (d [(k), (r)], d [(k), (s)]).

Step-5 If all the data points are in one cluster then stop, else repeat from step 2.

Advantages:

- It can produce an ordering of the objects, which may be informative for data display.
- Smaller clusters are generated, which may be helpful for discovery.

TEXTURE

Texture gives us information on structural arrangement of surfaces and objects on the image. Texture is not defined for a separate pixel; it depends on the distribution of intensity over the image. Texture possesses periodicity and scalability properties; it can be described by main directions, contrast, and sharpness. Texture analysis plays an important role in comparison of images supplementing the color feature. The most frequently used statistical features include, general statistical parameters calculated from pixels' intensity values, parameters calculated based on the co-occurrence matrices, texture histograms built upon the Tamura features.

One of the first methods for representing texture features of images was grey level co-occurrence matrices (GLCM) proposed by Haralick et al. [22]. Authors suggested 14 descriptors, including the angular second moment, contrast (variance, difference moment), correlation, and others. Each descriptor represents one texture property. Therefore, many works for example as described in [23], are devoted to selecting those statistical descriptors derived from the cooccurrence matrices that describe texture in the best way. In [24], firstly, transforming color space from RGB model to HSI model, and then extracting color histogram to form color feature vector. Secondly, extracting the texture feature by using gray co-occurrence matrix. Thirdly, applying Zernike moments to extract the shape features. Finally, combining the color, texture and shape features to form the fused feature vectors of entire image. Experiments on commonly used image datasets show that the proposed scheme achieves a very good performance in terms of the precision, recall compared with other methods.

A method is proposed [25] for efficient image retrieval that applies a weighted combination of color and texture to the wavelet transform, based on spatial-colour and second order statistics, respectively. The proposed descriptor is particularly useful for multi-resolution image search and retrieval.

IV. PROPOSED WORK

The proposed system design is given using figure 2 which is given in two main phases. First for train the system or storing the data into the database and second is used for accepting the user query and producing the search results. Therefore the entire system is described in three major modules first feature extraction, Query interfacing and finally the results listing.

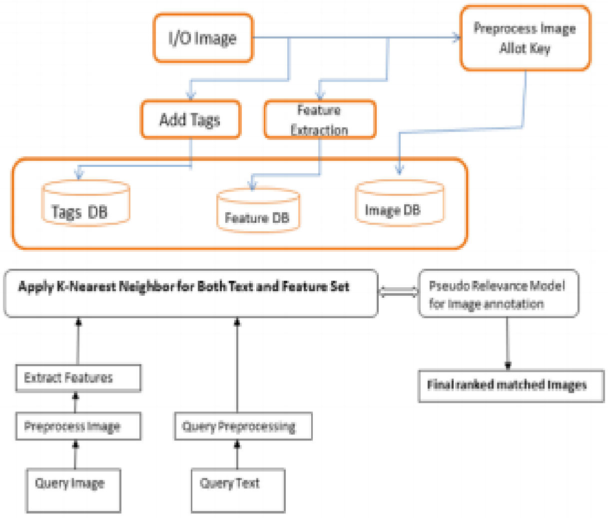

Fig.2. Proposed System

4.1. Feature extraction

The content based images are retrieved by their image properties such as image objects edges, color distributions and the image textures. Therefore all the tree image features are computed and normalized first which is stored in a database table for image feature representation. At the same time the image are also tagged with some kind of text which indicates the objects available in the input image during training phase. These tags are preserved separately in a table. But in order to recognize the image a key is assigned which is also preserved with the databases.

4.2. Query interface

As database is filled with the image contents the training session of the presented model is completed. Now for accepting the user query the system can accept the text query and image query also through the individual user interface.

4.3. Search outcomes

The user produced query is supplied to the KNN algorithm where the KNN having to inputs first the user query tokens and second the database of images, image features and the tag associated with images. Thus by finding the distance between the user query input and the data base scenarios the nearest distance images and their objects are recognized.

The basic features of the proposed work model are explained in this section. In addition of that their modular distribution for implementation of the CBIR model is also explained. The next section discussed the conclusion and the future extension of the presented work.

V. CONCLUSION

The Query clustering algorithm using agglomerative method helps to retrieve the images in large database. The effectiveness of the proposed framework compared with other presented retrieval algorithms. This algorithm gives more accurate results than the query mining algorithm. Experimental results show that user profiles which capture both the user's positive and negative preferences perform the best among all of the profiling strategies studied. This algorithm gives the better precision and recall values, which are helpful in determine the efficiency of search engine queries. In future work it can be done for voice recording and voice searching. And also in future, using ranking based image retrieval (RBIR) method can be done to provide ranking for each user query. Many times to give same query for image retrieval, the query will arrange priority based and the query easily retrieve the images.

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