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IMAGE RETRIEVAL FOR MULTI-IMAGE QUERIES HANDLING HIDDEN CLASSES

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ABSTRACT: The image retrieval system is used for browsing, searching and retrieving images from a large database of digital images. In the proposed system, Content-Based Image Retrieval (CBIR) handles the predefined classes using low level features. To improve the accuracy of the retrieval, color and texture features of the image is extracted, which is represented as color co-occurrence matrices. In retrieval, complexity of selecting a query object in single image query is high. To avoid this problem, multi-image query is used to perform the retrieval. Support Vector Machine (SVM) is used to construct the classifier for pre-defined classes. However, in a large-scale image collection, some image classes may be unseen. These unseen image classes are termed as hidden classes. In order to handle the hidden classes, the unclassified images are clustered, based on color and texture feature using K-means clustering algorithm. The queries associated with the hidden classes cannot be accurately answered using a traditional CBIR system. To handle these hidden classes, a robust CBIR scheme is proposed that incorporates a novel query detection technique, which is used to identify a query as a common query or a novel query. In this work, Majority Vote Rule and Bayes Sum Rule are applied to implement the image query detection technique. For a common query, a relevant predefined image class will be predicted and within the class the relevant images are ranked. For hidden classes, during the retrieval process the features of the query image are extracted, then matched with the centroid of the each cluster. Among these clusters, features extracted from the query image that are nearest to the centroid of the cluster is selected. Then the query image is compared with the nearest images to the centroid of the selected cluster and the more relevant images are ranked.

KEYWORDS: *CBIR, Support Vector Machine, Multi-image query, Novel query detection, hidden classes*

I. INTRODUCTION

The development of the multimedia technique, digital library and multimedia database leads to an increase in image databases. The rapid growth in the quantity and availability of digital images motivates research into automatic image retrieval. Image retrieval could be based on metadata or content. Most common methods of image retrieval searches the images using associated metadata such as keywords and text. Traditional information retrieval technologies can be easily applied for metadata-based image retrieval. However, metadata-based image retrieval may suffer from several critical problems, such as, the lack of appropriate metadata associated with images. The problems of metadata-based image retrieval inspire the research of content based image retrieval. Content based image retrieval (CBIR) provides a promising way to address the problems of metadata-based image retrieval. It is aimed to search the images using the content of images, which are usually characterized by visual features, such as, color, texture and shape. In practice, CBIR could be complementary component to metadata-based image retrieval. This system, propose a color image retrieval method based on texture and color using color co-occurrence matrix. First, extract the texture and color features of the image is extracted, which is represented as color co-occurrence matrices. Color information, such as components and distribution, are the important factors of color image. The feature obtained not only reflects the texture correlation but also represents the color information.

II. RELATED WORK

Image classification improves the accuracy and speed of a content based image retrieval (CBIR) system. Images in a collection can be categorized by supervised image classification using predefined image classes. For a given query, the retrieval results of a CBIR system are generated by first locating the most relevant image followed by ranking the images within the class. It should be noted that image classification is not necessary for all CBIR systems. A CBIR system can be entirely based on similarity retrieval without any classes.

Jun Zhang et al [1] proposed a Robust image retrieval with hidden classes. The aim of various CBIR systems is to search images by analyzing their content. For the purpose of content-based image retrieval (CBIR), image classification is important to improve the retrieval accuracy and speed of the retrieval process. However, the CBIR systems that employ image classification suffer from the problem of hidden classes. The queries associated with hidden classes cannot be accurately answered using a traditional CBIR system. To address this problem, a robust CBIR scheme is proposed that incorporates a novel query detection technique and a self-adaptive retrieval strategy. A number of experiments carried out on the two popular image datasets demonstrate the effectiveness of the proposed scheme. However, compared to the conventional scheme, this scheme can achieve over only 10% improvement in its retrieval performance.

Hatice Cinar Akakin and Metin N. Gurcan [2] proposed a Content-based Microscopic Image Retrieval System for Multi - Image Queries. This system describe the design and development of a multi-tiered CBIR system for microscopic images utilizing a reference database that contains images of more than one disease. Proposed CBIR system uses a multi-tiered approach to classify and retrieve microscopic images involving their specific subtypes which are mostly difficult to discriminate and classify. This system enables both multi-image query and slide-level image retrieval in order to protect the semantic consistency among the retrieved images. New weighting terms, inspired from information retrieval (IR) theory, are defined for multiple-image query and retrieval. Performance of the system was tested on a dataset including 1666 imaged high power fields (HPF) extracted from 57 Follicular Lymphoma (FL) tissue slides with three subtypes and 44 Neuroblastoma (NB) tissue slides with four subtypes, where each slide is semantically annotated according to their subtypes by expert pathologists. By using leave-one-slide out testing scheme, the multi-image query algorithm with the proposed weighting strategy achieves about 93% and 86% of average classification accuracy at the first rank retrieval, outperforming the image-level retrieval accuracy by about 38 and 26 percentage points, for FL and NB diseases, respectively.

Xiang-Yang Wang et al [7] proposed a new content-based image retrieval technique using color and texture information, which achieves higher retrieval efficiency. Firstly, the image is transformed from RGB space to opponent chromaticity space and the characteristics of the color contents of an image is captured by using Zernike chromaticity distribution moments from the chromaticity space. Secondly, the texture features are extracted using a rotation-invariant and scale-invariant image descriptor in Contour let domain, which offers an efficient and flexible approximation of early processing in the human visual system. Finally, the combination of the color and texture information provides a robust feature set for color image retrieval. Experimental results show that the existing color image retrieval is more accurate and efficient in retrieving the user-interested images.

Wang Xing-yuan et al [6] proposed an effective method for color image retrieval based on texture, which uses the color co-occurrence matrix to extract the texture feature and measure the similarity of two color images. Due to the color information such as components and distribution is also taken into consideration, the feature obtained not only reflects the texture correlation but also represents the color information. As a result, our proposed method is superior to the gray-level co-occurrence matrix method and color histogram method, and it enhances the retrieval accuracy which is measured in terms of the recall andprecision in the meanwhile. Especially it provides better retrieval performance only on texture images.

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Samuel RotaBul et al [5] proposed a novel approach to content-based image retrieval with relevance feedback, which is based on the random walker algorithm introduced in the context of interactive image segmentation. The ranking score for each unlabeled image is computed as the probability that a random walker starting from that image will reach a relevant seed before encountering a non-relevant one.

M.E. ElAlami [4] proposed an image retrieval framework based on a rule base system. The proposed framework makes use of color and texture features, respectively called color co-occurrence matrix (CCM) and difference between pixels of scan pattern (DBPSP). These features are used to perform the image mining for acquiring clustering knowledge from a large empirical images database. Irrelevance between images of the same cluster is precisely considered in the proposed framework through a relevance feedback phase followed by a novel clustering refinement model. The images and their corresponding classes pass to a rule base system for extracting a set of accurate rules. These rules are pruning and may reduce the dimensionality of the extracted features. The advantage of this framework is reflected in the retrieval process, which is limited to the images in the class of rule matched with the query image features.

Qasim Iqbal et al proposed an effective method for Feature Integration, Multi-image Queries and Relevance Feedback in Image Retrieval. This paper explore the effect of feature integration, multi-image queries, and relevance feedback in enhancing the performance of an image retrieval system. Weighted integration of structure, color and texture features is studied. In addition, we propose a methodology of retrieval consisting of multiple query images, as opposed to the traditionally used model of a single query image. Two different mechanism of relevance feedback are also proposed and analyzed. Integration of features and feedback significantly improves the performance of the retrieval system.

III. PROPOSED SYSTEM

The aim of proposed system is to avoid the use of textual descriptions for image retrieval. The CBIR system retrieves the images based on similarities in their contents (textures, colors, shapes etc.) to the query image. The system is designed to use the multi-image query to perform the image retrieval. The features of an given training samples are extracted. Support Vector Machine (SVM) is used to construct the classifier for pre-defined classes. To improve the accuracy of the retrieval, color and texture features of the images are extracted, which is represented as the color co-occurrence matrices. The color and texture features of the query image is extracted and given to the set of SVM classifiers. According to the class, the relevant images are retrieved from the pre-defined classes. Also it performs novel query detection and perform image retrieval for hidden classes.

1) Feature Extraction and Classifier Construction: Using color and texture features of the training samples, the classifiers are constructed. Divide a color image into N*N blocks. Using mosaic dominant color extraction algorithm calculate the dominant color c (i,j) for each block. Color and texture features of the image are extracted, which is represented as color co-occurrence matrices. For two arbitrary bloc T(i, j) and

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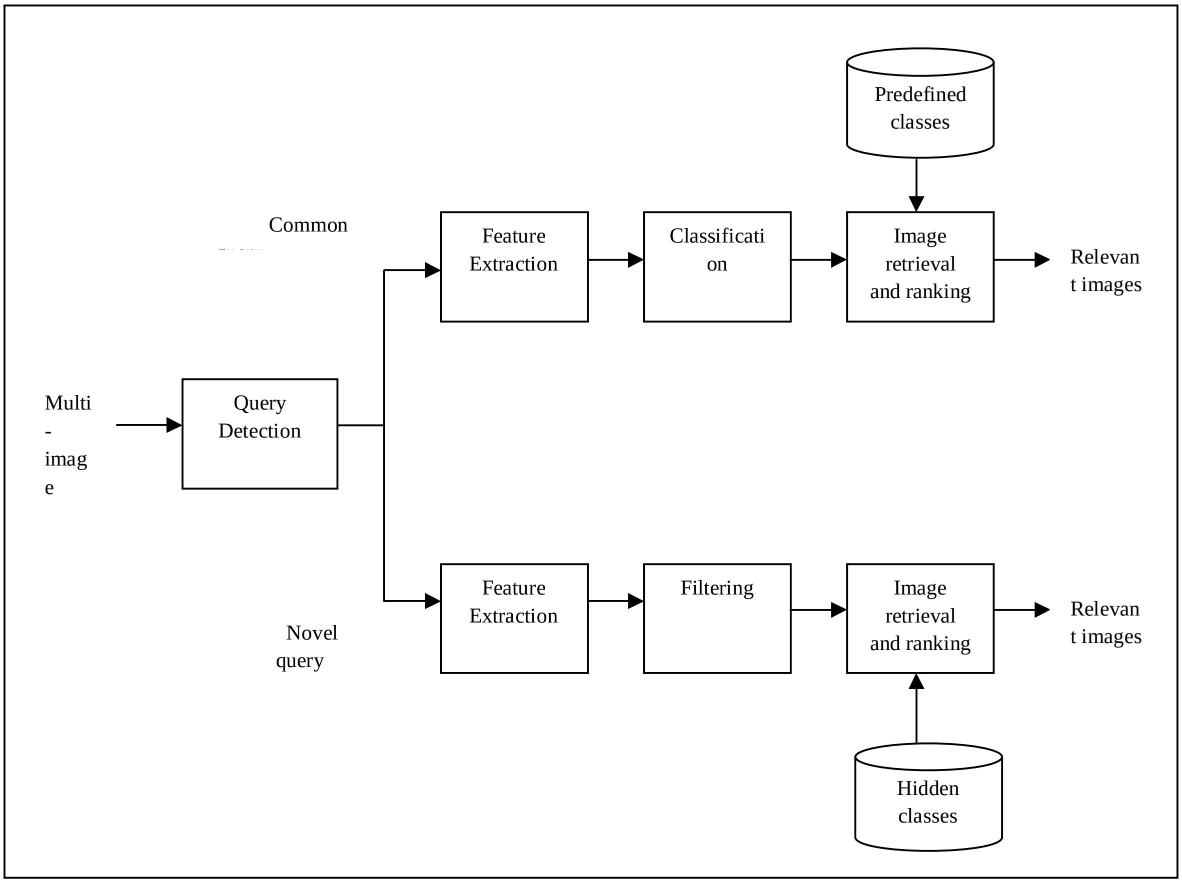

Fig. 1 Multi- query image retrieval

T(k, l)(| i−k|=1 and |j−l|=1) which satisfy the criterion of 8-connectivity, if their corresponding dominate color C(i, j) and C(k, l) are correlative, blocks T(i, j) and T(k, l) are color connectivity. Divide the blocks of image T into color connectivity region set S= {Ri}(1≤i≤M) according to the criterion of 8-connectivity, where M is the number of color connectivity regions. Extract the R,G,B and I components of the image T, and each component is quantized into D=8.

For each color connectivity region, calculate the normalized co-occurrence matrix for each R,G,B and I component, and then extract the following statistical value from each matrix:

$$E = \sum_{i=1}^{D}\sum_{j=0}^{D}[m(i,j)]^2 \qquad (1)$$

$$I = \sum_{i=0}^{D}\sum_{j=0}^{D}(i-j)^2\, m(i,j) \qquad (2)$$

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$$P = -\sum_{i=0}^{D}\sum_{j=0}^{D} m(i,j)\log[m(i,j)] \qquad (3)$$

$$H = \sum_{i=0}^{D}\sum_{j=0}^{D}\frac{m(i,j)}{1+(i-j)^2} \qquad (4)$$

where E denotes energy, I represents inertia, P denotes entropy, H represents uniformity. They are commonly used texture descriptors and can effectively reflect the texture feature.

Calculate the normalized feature vector of image T, which is defined as follow,

F = [FR, FG, FH, FI] (5)

A linear Support Vector Machine (SVM) classifier is used to construct the set of SVM classifiers. The input of the classifier construction is color and texture features of the positive and negative samples, which is used to train the classifier. Given a set of training samples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other.

Given training data *D*, a set of *n* points of the form

$$D = \{(x_i, y_i) | X_i \in R^P, Y_i \in \{-1,1\}\}_{i=0}^{n} \qquad (6)$$

where the y_i is either 1 or −1, indicating the class to which the point $\mathbf{x}_i$ belongs. The training sets are linearly separable using linear kernel function. If the training data are linearly separable, then two hyperplanes are selected in a way that they separate the data and there are no points between them, and then try to maximize their distance. The region bounded by them is called "the margin". These hyperplanes can be described by the equations,

w.x-b=1 (7)

and

w.x-b=-1 (8)

Finally the classifications of images have been processed. The output of the classifier construction is a set of support vectors.

2) Classification of Images: The testing samples are used as the input, which is taken from the image database. Color and texture features are extracted from those samples. Then the classifications of images have been done using set of classifiers. Finally it outputs the class of images. That class of the images is used to perform the image retrieval.

3) Query detection technique: The multi-image query is used to perform the retrieval from the database. The features of the query image is extracted and given into the set of SVM classifiers. The classifier outputs the class the image query. Based on the class the images are retrieved from the pre-defined classes and it is ranked based on similarities. Finally the most relevant images are ranked. From that the top most relevant images are displayed as output of the given query image.

4) Retrieval for Common Query: *Th*e single image query is used to perform the retrieval from the database. The features of the query image is extracted and given to the set of SVM classifiers. The classifier outputs the class of the image query. Based on the class the images are retrieved from the pre-defined classes and it is ranked based on similarities. Finally the most relevant images are ranked. From that the top most relevant images are displayed as output of the given query image.

5) Image Retrieval for Novel Query: Novel query detection technique is used to identify the query image as a common query or novel query. In order to handle the hidden classes, the unclassified images are clustered, based on color and texture feature using K-means clustering algorithm. During the retrieval process the features of the query image are extracted, then matched with the centroid of the each cluster. Among these clusters, features extracted from the query image that are nearest to the centroid of the cluster is selected. Then the query image is compared with the nearest images to the centroid of the selected cluster and the more relevant images are ranked.

5.1) Image filtering: Since the novel query cannot be answered by any predefined image class, it is likely the images in the predefined image classes are not relevant to the novel query and can be filtered out. The prepared image classifiers,

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{f1(x), . . . , fM(x)}, can be utilized to produce a set of images, W, from the whole image collection. The images in W are not relevant to the predefined image classes. These images will be used to answer the novel query. The filtering rule is that,

put x in W. This image filtering process can be conducted off-line, i.e., W can be created in the stage of preprocessing.

5.2) Ranking for a novel query: In this paper, we cast image ranking for a novel query as a binary classification problem. The query images are used as the positive samples and the training samples for the predefined image classes are used as the negative samples. All positive and negative samples are combined to train a classifier, such as a SVM, for image ranking. However, the positive and negative samples are unbalanced, which influences the accuracy of a SVM. We apply the asymmetric bagging strategy to construct an ensemble of SVMs and combine the outputs for image ranking.

IV. EXPERIMENTAL RESULTS

The Caltech 101 data set consists of a total of 9146 images, split between 101 different object categories, as well as an additional background category. Each object category contains between 40 and 800 images on average. Common and popular categories such as faces tend to have a larger number of images than less used categories. Each image is about 300x200 pixels in dimension. Images of oriented objects such as airplanes and motorcycles were mirrored to be left-right aligned, and vertically oriented structures such as buildings were rotated to be off axis. The Caltech 101 data set has been used to train and test several Computer Vision recognition and classification algorithms.

In the experiment, we use the database consists of nearly 400 images from large varieties. The types of images in the database include airplane, bus, beach, human beings. Images with different orientations have also been included.

In this experiment, to the query image 20 images are retrieved, among these 19 relevant images are retrieved. It shows the accuracy of the proposed system compared with conventional scheme.

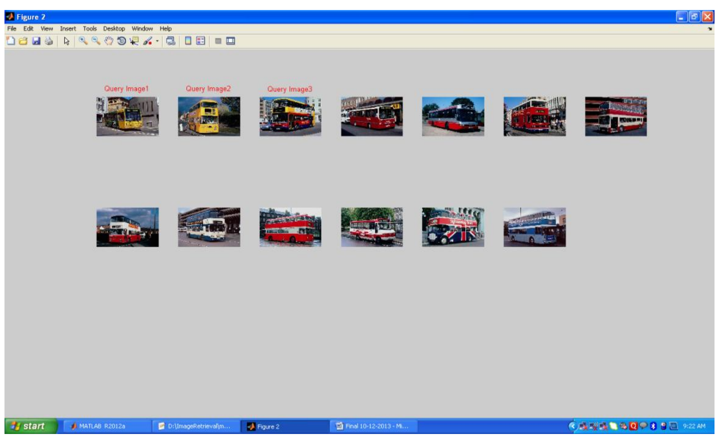

Fig 2 Retrieval results for the query images – Bus

The performance of the proposed method is evaluated quantitatively to get a systematic evaluation. The retrieval performance is measured by computing a Precision-Recall curve.

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Table 1 Retrieval performance – Precision

Classes of the image	Precision (P)	
	Single image query	Multi-Image Query
Bus	0.85	1.0
Beach	0.8	0.85
Buildings	0.75	0.9
Human Being	0.8	0.95

Table 2 Retrieval performance – Recall

Classes of the image	Recall(R)	
	Single image query	Multi-Image Query
Bus	0.8	0.9
Beach	0.75	0.8
Buildings	0.7	0.87
Human Being	0.7	0.85

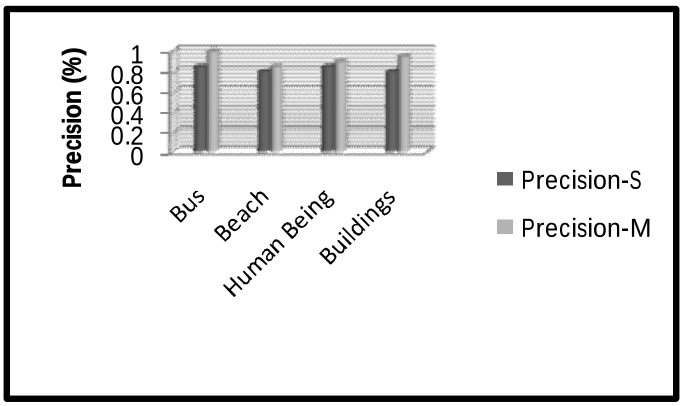

Fig. 3 Retrieval performance- Image classes Vs Precision

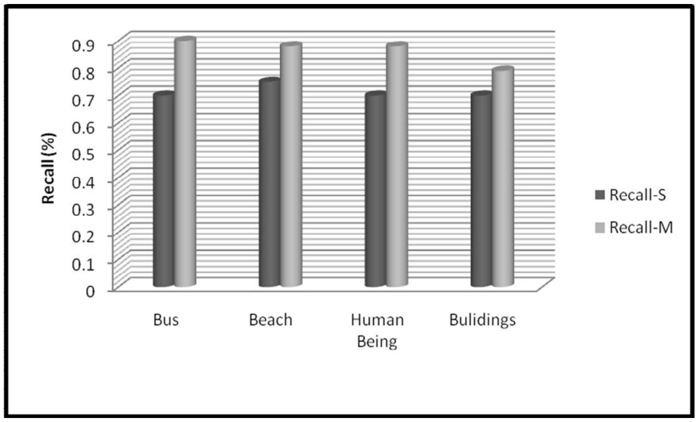

Fig. 4 Retrieval performance - Image classes Vs Recall

V. CONCLUSION AND FUTURE WORK

The proposed image retrieval system consists of feature extraction and classifier construction for training samples, classification of images, novel query detection, retrieval for common query images, retrieval for novel query images. First, feature extraction and classifier construction for testing sample is constructed. Second, classification of the image has been done using SVM classifier. Third, in retrieval for multi- image query, the features of the query image is extracted and given into the set of SVM classifiers. The classifier outputs the class the image query. Based on the class the images are retrieved from the pre-defined classes and it is ranked based on similarities. Then the system performs a novel query detection technique to find whether the given query image belongs to which class. Also this system performs the image retrieval for multi-image query, which are not similar in poses. In comparison with state-of-the art methods, the proposed method is simple and provides better retrieval performance for multi-image query.

REFERENCES

[1] Jun Zhang , Lei Ye , Yang Xiang , Wanlei Zhou (2013), “Robust Image Retrieval With Hidden Classes” , www.elsevier.com,School of Information Technology, Deakin University, Melbourne, Australia, Computer Vision and Image Understanding, Vol.117, pp.670–679.

[2] Hatice Cinar Akakin and Metin N. Gurcan (2013) “Content-based Microscopic Image Retrieval System for Multi - Image Queries” IEEE Trans Inf Technol Biomed. 2012 July ; 16(4): 758–769.

[3] Mr. Shrikant, J. Honade (2013), “Height Weight and Body Mass Indux Measurement Using Matlab”, International Journal of Advanced Research in Engineering and Technology, vol 4, issue 5, , pp. 35-45.

[3] Ke Lu , Jidong Zhao (2011) , “Neighborhood preserving regression for image retrieval”, www.elsevier.com, School of Information Technology , Neurocomputing 74 (2011) pp.1467–1473.

[4] M.E. ElAlami (2011) “Supporting image retrieval framework with rule base system”, www.elsevier.com, School of Information Technology, Computer Standards & Interface, Knowledge-Based Systems 24 pp. 331–340.

[5] Samuel Rota Bulo , Massimo Rabbi, Marcello Pelillo (2011), “Content-based image retrieval with relevance feedback using random walks”, www.elsevier.com, School of Information Technology,Pattern Recognition 44 pp.2109–2122.

[6] Saja Usman, Dimpil Shajahan (2014),”A Review on Different Glaucoma Detection Methods ”, International Journal of Advanced Research in Engineering and Technology, vol 5, issue 2, , pp. 95 – 100.

[7] Xiang-Yang Wang , Hong-Ying Yang , Dong-Ming Li (2013) “A new content-based image retrieval technique using color and texture information” Computers and Electrical Engineering pp.746–761.

[7] Ying Liua,, Dengsheng Zhanga, Guojun Lua,Wei-Ying Mab (2007) “A survey of content-based image retrieval with high-level semantics” Pattern Recognition, pp.262 – 282.

[8] WangXing-yuan , ChenZhi-feng , YunJiao-jiao (2011),“An effective method for color image retrieval based on texture”, www.elsevier.com, School of Information Technology, Computer Standards & Interface pp. 31-35.