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CONTENT BASED IMAGE RETRIEVAL USING SEMI SUPERVISED BIASED DISCRIMINANT ALGORITHM

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ABSTRACT

An image Retrieval is a process of browsing, searching and retrieving images from a large database of digital images. Image database is a collection of large number of different kinds of images such as textured, non- textured, natural, artificial and cartoons etc. When a query image is submitted, its low-level as well as high level visual features are extracted. Then, all images in the database are sorted based on a similarity metric. If the user is satisfied with the result, the retrieval process is ended. User satisfaction is done by means of relevance feedback (RF) algorithm. In order to retrieve the unsampled images effectively we proposed semi supervised biased discriminant Euclidean embedding(semi BDEE).This method increase the stability and accuracy on dfferent kind of image database.

INTRODUCTION

The need for the retrieval system is increased to the excessive growth of multimedia contents. If the user is not satisfied with the retrieval image he can label some images as positive feedbacks and some images as negative feedbacks. Using this feedback process, the system is trained based on machine learning using the embedded RF algorithm. Then, all the images are re-sorted based on the recalculated similarity metric. Generally in a CBIR RF system images are represented by the three main features like colour space and a 9 dimensional colour moment feature in Luv colour space are both employed. For the texture feature a pyramidal wavelet transform (PWT) is extracted from the Y component in YCbCr space. Every image is decomposed by the traditional pyramid-type wavelet transform with Haar wavelet.

BDEE precisely models both the intraclass geometry and interclass discrimination and also based on low-level visual features. For unlabelled samples, a manifold regularization-based item is introduced and combined with BDEE to form semi-supervised BDEE, or semi-BDEE. For the proposed BDEE and semi-BDEE, it is compared with the conventional RF algorithm and show a significant improvement in terms of accuracy and stability. Moreover, it is also desirable to develop image retrieval tools to browse and search images effectively and efficiently because of the explosive growth of personal image records and image records on the Internet. In order to discover the intrinsic coordinate of image low level visual features, parameterize samples in the original high-dimensional ambient space based on the proposed Semi-Biased Discriminant Euclidean Embedding algorithm (BDEE).The paper is organised as follows. In section II, image retrieval model is discussed. In Section III, content based image retrieval is explained. In section IV, biased discriminant Euclidean embedding is discussed. In section V, results are analysed. In section VI, coclusion and future work is presented.

IMAGE RETRIEVAL MODEL

The proposed Semi-BDEE, use the projection matrix to project all samples including the query image, the positive samples, the negative samples, and the rest images in the database to the low-dimensional subspace spanned. Afterwards, each of these images are sorted according to the Euclidean distance with respect to the pseudo query, which is the mean of the query image with all positive samples.CBIR assumes that the user expects the best possible retrieval results after each relevance feedback iteration, i.e., the search engine is required to return the most semantically relevant images based on the previous feedback samples. With the proposed system, it can embed many kinds of relevance feedback algorithms easily.

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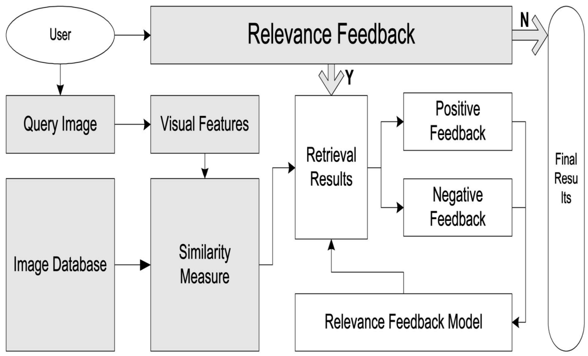

Figure 1. Image retrieval system model

From Figure. 1, when a query (image) is given, the visual features are extracted. Then, all images in the database are sorted based on a similarity metric. If the user is satisfied with the results, the retrieval process is ended. However, most of the time, the relevance feedback is needed because of a poor retrieval performance. The user labels some top images as positive feedback samples or negative feedback samples. Using these feedback samples, a relevance feedback model can be trained based on certain machine learning algorithms. The similarity metric can be updated as well as the relevance feedback model. Then, all the images are resorted based on the recalculated similarity metric. If the user is not satisfied with the results, the relevance feedback process will be performed iteratively. All the images in the database are sorted relevant images as positive feedback samples and query irrelevant images as negative feedback samples. Using these feedback samples with or without selected unlabelled samples, an RF model can be trained based on certain machine learning algorithms.

For the proposed Semi-BDEE, a projection matrix based on the Euclidean measure is used. However, most of the time, RF is required because of a poor retrieval performance. The similarity metric and the RF model can be updated. Then, all the images are resorted based on the recalculated similarity metric. In the experiment, 500 queries are first randomly selected from the data, and then relevance feedback is automatically performed by the computer: All query relevant images (i.e., images with the same concept as the query) are marked as positive feedback samples in the top 20 images and all the other images are marked as negative feedback samples.In general, have around 5 to 8 images as positive feedback samples. Because the visual features cannot well describe semantic contents, a system usually asks the user to mark one or two screen shots of images in the current retrieval process. Meanwhile, for some applications, the user might like to label only a small number of feedback samples and expect to get the best results wherever the query process is terminated. However, some other users might like to cooperate with the system and provide many (screens of) positive/negative examples. For the proposed Semi-BDEE, the projection matrix is query image with all positive samples in. If the retrieved result is not satisfied, the RF process is performed iteratively.

CONTENT BASED IMAGE RETRIEVAL

The most common method for comparing two images in content based image retrieval using an image distance measure. An image distance measure compares the similarity of two images in various dimensions such as color, texture, shape, and others. For example a distance of 0 signifies an exact match with the query, with respect to the dimensions that were considered. As one may intuitively gather, a value greater than 0 indicates various degrees of similarities between the images. Search results then can be sorted based on their distance to the queried image.

Color: Computing distance measures based on color similarity is achieved by computing a color histogram for each image that identifies the proportion of pixels within an image holding specific values (that humans express as colors). Current research is attempting to segment color proportion by region and by spatial relationship among several color regions. Examining images based on the colors they contain is one of the most widely used techniques because it does not depend on image size or orientation. Color searches will usually involve comparing color histogram though this is not the only technique in practice.

Texture: Texture measures look for visual patterns in images and how they are spatially defined. Textures are represented by texels which are then placed into a number of sets, depending on how many textures are detected in the image. These sets not only define the texture, but also where in the image the texture is located.

Texture is a difficult concept to represent. The identification of specific textures in an image is achieved primarily by modeling texture as a two-dimensional gray level variation. The relative brightness of pairs of pixels is computed such that degree of contrast, regularity, coarseness and directionality may be estimated. However, the problem is in identifying patterns of co-pixel variation and associating them with particular classes of textures such as ``silky, or ``rough.

Shape: Shape does not refer to the shape of an image but to the shape of a particular region that is being sought out. Shapes will often be determined first applying segmentation or edge detection to an image. Other methods like use shape filters to identify given shapes of an image. In some case accurate shape detection will require human intervention because methods like segmentation are very difficult to completely automate.

IV.BIASED DISCRIMINANT EUCLIDEAN EMBEDDING

Image retrieval has become one of the most active research directions in the multimedia information processing because of the rapidly increasing requirements in many designs. practical applications like architectural design, museum management, education and fabric

Relevance feedback (RF) has been demonstrated to be a powerful tool which involves the user in the loop to enhance the performance of CBIR. Popular RF schemes can exhibit some general limitations of over sensitivity to subjective labelling by users and the inability to accumulate knowledge over different sessions and users. The conventional process of RF is as follows:

1. From the retrieved images, the user labels a number of relevant samples as positive feedbacks, and a number of irrelevant samples as negative feedbacks.
2. The CBIR system then refines its retrieval procedure based on these labelled feedback samples to improve retrieval performance, learning, Support Vector Machine (SVM),Random sampling based methods and Feature selection-based method.

Recently, many RF methods have been introduced and classified as Subspace This method uses a novel algorithm is used, which precisely models both the intraclass geometry and interclass discrimination and never meets the under sampled problem. That is in the low-dimensional space, distances between positive samples and negative samples should be as large as possible while distances between positive samples should be as small as possible,and the local geometry of positive samples should be preserved as much as possible by keeping linear reconstruction coefficients obtained. The former part is called the discrimination preservation and the latter is called the local geometry preservation, hence this proposed algorithm is called as Biased Discriminant Euclidean Embedding (BDEE).

In the low-dimensional space, distances between positive samples and negative samples should be as large as possible while distances between positive samples should be as small as possible. To implement the discrimination preservation in BDEE, shown in Fig.1.3.1,it is expected that positive samples should be far away from negative samples and the distances between average weighed pairwise distance between two positive samples.

A.FEATURE SELECTION AND EPRESENTATION

In terms of feature selection, while most CBIR systems use traditional image features such as color histogram or moments, texture, shape, and structure features, there are alternatives. Tieu and Viola (Tieu and Viola 2000) used more than 45,000 highly selective features., and a boosting technique to learn a classification function in this feature space. The features were demonstrated to be sparse with high kurtosis, and were argued to be expressive for high-level semantic concepts. Weak 2-class classifiers were formulated based on Gaussian assumption for both the positive and negative. In its short history, relevance feedback developed along the path from heuristic-based techniques to optimal learning algorithms, with early work inspired by term weighting and relevance feedback techniques in document retrieval (Salton 1989). These methods proposed heuristic formulation with empirical parameter adjustment, mainly along the line of independent axis weighting in the feature space. Different image features need to be normalized to have comparable statistics, say normal distribution. Not surprisingly, this normalization can also be extended to a transformation of the feature space. From a discrimination point of view, the optimal normalization shall be the transform that separates all the semantically meaningful classes in the dataset while clusters within each class.

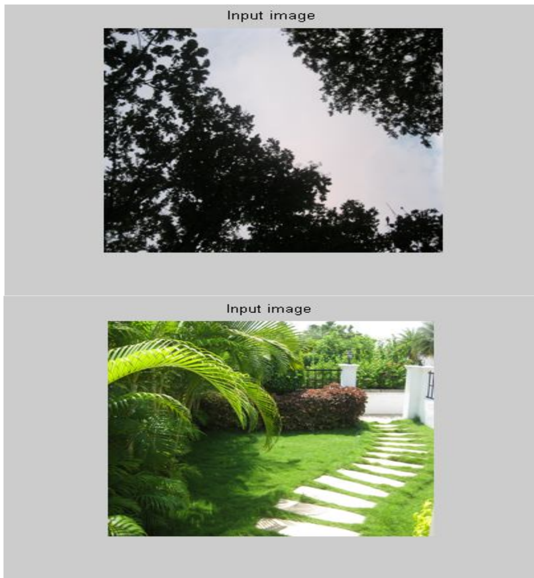

Figure .2 Pair of input images from an outdoor sequence

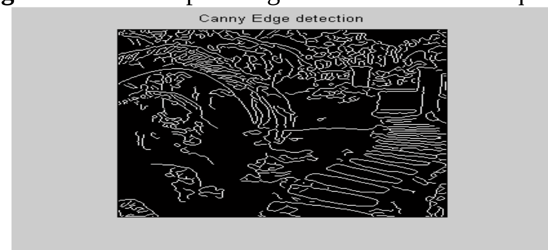

Figure 3 Unlinked Canny edges for the outdoor images

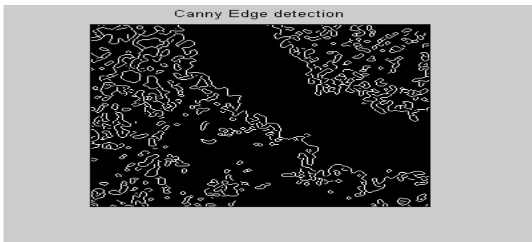

Figure 4 Linked Canny edges for the outdoor images

This is illustrated in Figure 4 for the Canny edge operator, where the above- and below-threshold edges are represented respectively in black and grey. Note that in the bushes, some, but not all, of the edges are readily matchable by eye. After hysteresis has been undertaken, followed by the deletion of spurs and short edges, the application of a junction completion algorithm results in the edges and junctions shown in Figure 4.3, edges being shown in grey, and junctions in black. In the bushes, very few of the edges are now readily matched. The problem here is that of edges with responses close to the detection threshold: a small change in edge strength or in the pixellation causes a large change in the edge topology. The use of edges to describe the bush is suspect, and it is perhaps better to describe it in terms of feature-points alone.

B.DIRECT KERNEL BIASED DISCRIMINANT ANALYSIS (DKBDA) AND ITS INCREMENTAL VERSION

The regularization method to solve the SSS problem significantly improve the performance of CBIR RF and utilize the direct idea to the BDA algorithm in the kernel feature space. This direct method is proposed based on all positive examples are alike and each negative example is negative in its own way. The approach is named as the direct kernel BDA (DKBDA). DKBDA is motivated by: (a) the fact that direct LDA (DLDA), recently developed for face recognition, has made some advances;

(b) Unlike face recognition, image retrieval deals with diverse images, so the nonlinear properties of image features should be considered because of the success of kernel algorithms in pattern recognition.

EXPERIMENTAL RESULTS

In this section we report the results of a large number of experiments in which we took the CBIR platform described in the previous section and compared the performance between KDBA, CSM, and our new DKBDA algorithms for RF. For the experiments we used part of the Corel image database, a real world database comprising 10,800 images.

SIMULATION RESULT FOR RGB TO HSV

The input image is RGB.Hue,Saturation and Value histogram is done and RGB image is converted into HSV image and the pixel values are also changed.

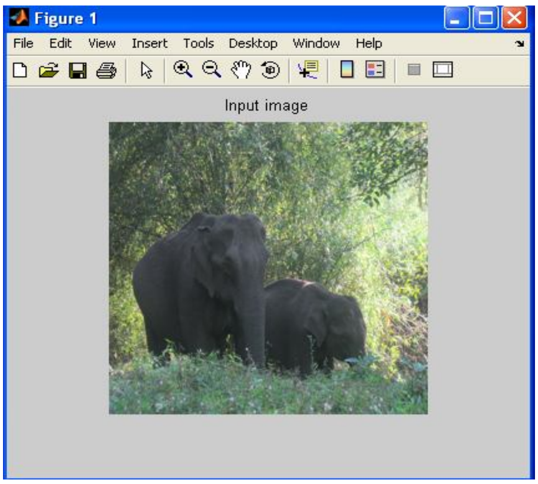

Figure .5 Input image

Here the hue, Saturation and value histogram values are obtained.

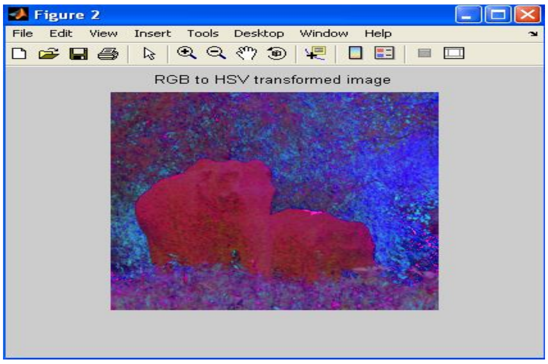

Figure .6 RGB to HSV transformed image

B.SIMULATION RESULT FOR TEXTURE EXTRACTION

Using the pyramidal wavelet transform component is extracted from the YCrCb space.It results in a feature vector of 24 values.

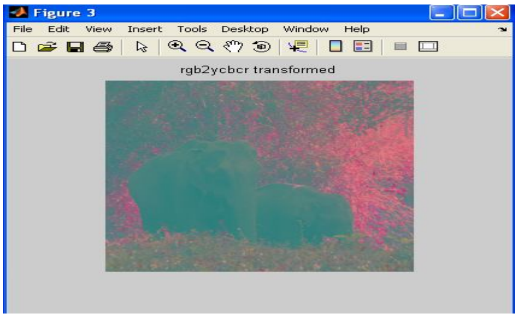

Fig.7 RGB to yCbCr transformed image

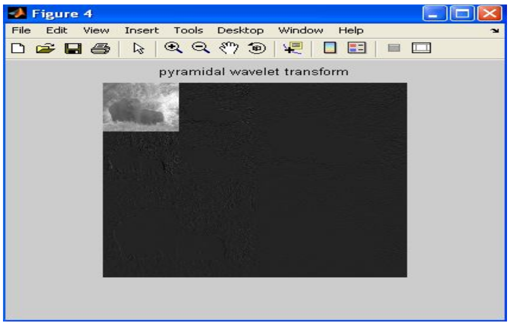

Figure 8 Pyramidal Wavelet Transform

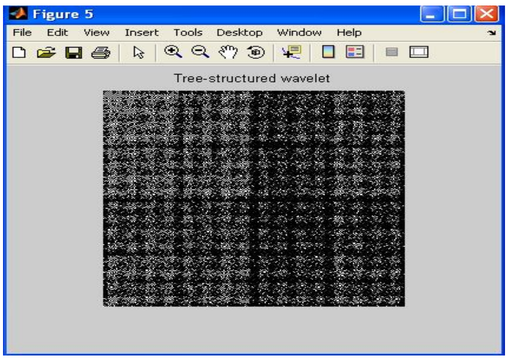

Figure 9 Tree Structured Wavelet Transform

The transform is separated into many energy levels.

SIMULATION RESULT FOR SHAPE LCULATION

In the shape calculation, the edges are detected using Canny Edge Detector.

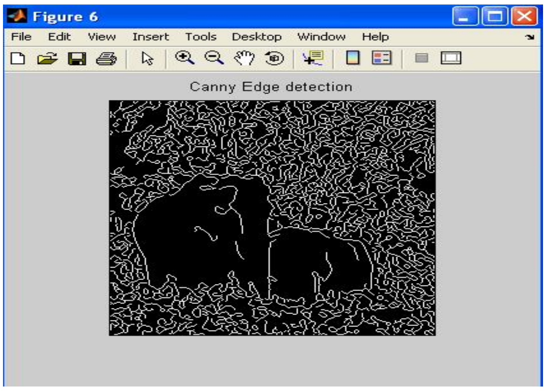

Figure 10 Canny Edge detection

In the shape histogram, number of pixel values is taken in the vertical axis and brightness value in the horizontal axis.

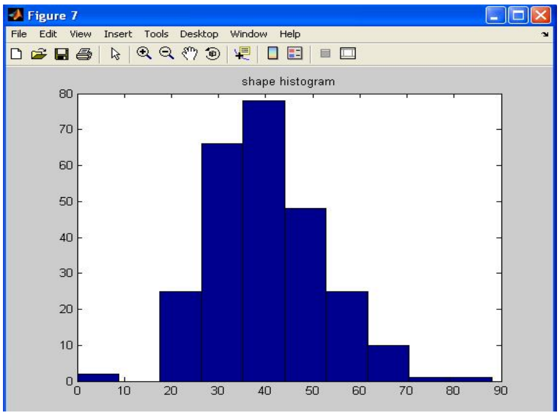

Figure 11 Shape Histogram

SIMULATION RESULTS USING GUI

The test image is given in the graphical user interface.

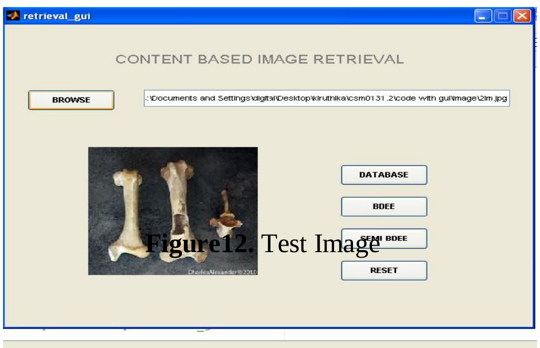

Figure12. Test Image

The database images are given using GUI.

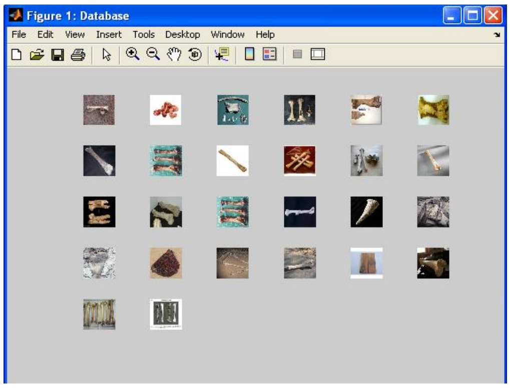

Figure13. Database Images

The test image is compared with images in the database and the images are retrieved according to BDEE and SEMI-BDEE algorithm.

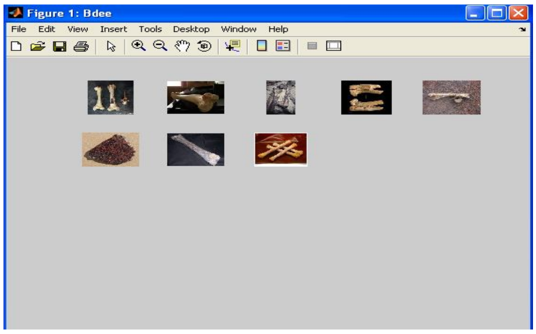

Figure14. Image Results for BDEE

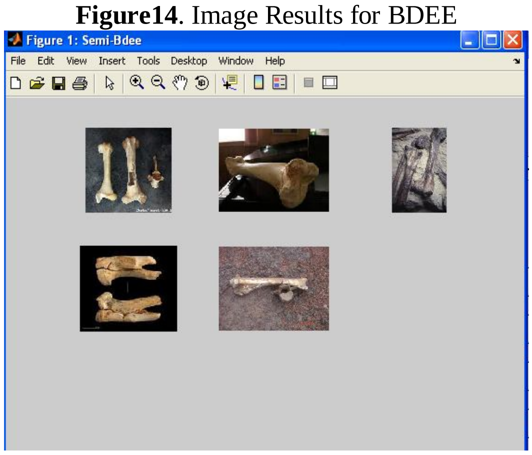

Figure.15 Image Results for SEMI-BDEE

CONCLUSION AND FUTURE SCOPE

BDEE precisely models both the intraclass geometry and interclass discrimination and never meets the undersampled problem. To consider unlabelled samples, a manifold regularization-based item is introduced and combined with BDEE to form the semi-supervised BDEE, or semi-BDEE for short. To justify the effectiveness of the proposed BDEE and semi-BDEE, it is compared against the conventional RF algorithms and show a significant improvement in terms of accuracy and stability based on a subset of the Corel image gallery. In addition, BDEE's semi-supervised extension also considers the unlabelled samples so the relevance feedback performance is further improved. Thus the semi BDEE retrieves most relevant images than BDEE with low level visual features.

Further research will be focused on simplification of the algorithm which attempt to avoid the calculation of low level visual features manually and images are compared with five or more query images.

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