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Image and Information Retrieval Based on Multi-Feature Similarity Score Fusion Using Genetic Algorithm

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Abstract: *Online Navigation behaviour grows each passing day, due to the interest of people in digital images is growing day by day; so the Users in many professional fields are exploiting the opportunities offered by the ability to access and manipulate remotely-stored images in all kinds of new and exciting ways but extracting information intelligently from a large image database, is a difficult issue and most commonly the irrelevant data's which are not related to our search will be retrieved. This paper approaches a new method, to achieve high efficiency and effectiveness of Content-Based-Image-Retrieval in large scale image data. We achieve effectiveness via extracting the colour and texture features by combining colour feature and GLCM as well as CCM separately depending on the former, image retrieval based on multi feature fusion is achieved by using normalized Euclidean distance classifier. In terms of efficiency we propose a method GA (Genetic Algorithm) to learn efficiency of our proposed method. If we click any relavant image details we can get it in pdf file or word document which contains the informations about the particular image This technology used in medical, Photoshop and web field.*

Keywords: *Content Based Image Retrieval, GLCM, CCM, GA, information retrieval.*

1. Introduction

In today's world more and more multimedia Information is stored in databases like images audio and video. An image may be better or more effective than a substantial amount of text. It also aptly characterizes the goals of visualization where large amounts of data must be absorbed quickly and it is a picture is worth of thousand words. If we use text for retrieving/searching an image what happens is- we can't write whole description of image this is one thing and if the image contains geographical data then manual keyword description are not possible ex: Google earth contains geographical data. So then why to go for this is because- It is cultural language dependent and is not possible to describe every image in database. Keyword matching will not give most relevant images. As a result, a number of powerful image retrieval algorithms have been proposed to deal with such problems over the past few years. Content-Based Image Retrieval (CBIR) is the mainstay of current image retrieval systems. CBIR operates on a totally different principle, retrieving/Searching stored images from a collection by comparing features automatically extracted from the images themselves. The commonest features used are mathematical measures of colour, texture or shape **(**basic**)**. A system (CBIR) allows users to formulate queries by submitting an example of the type of image being sought (input), though some offer alternatives such as selection from a palette or sketch input we can also select colour textures or any other visual information. The system then identifies those stored images whose feature values match those of the query most closely and displays thumbnails of these images on the screen. Although CBIR systems are queried by image content, a raw query image still needs to be formulated into an abstract form to execute it efficiently. Since end users, in general, do not know the make-up (kinds of images) of the image database and the content representation and search techniques used in the environment (what types of features and indexing methods are employed), it is hard for them to choose an appropriate query at the first trial. Therefore, the query formulation process is treated as a series of tentative trials until the target images are found. Most researchers strive to develop a new RF technique which can attain better retrieval performance than the existing ones. Because most existing methods refine the query again and again by analyzing the specific relevant images picked up by the users. Here we propose a new method FFE for improving efficiency of the relevance feedback based image retrieval technique. In this Approach we convert image feature vectors to weighted- term vectors and extract the frequently occurred feature vectors by implementing relevance feedback technique in content-based image retrieval to demonstrate the efficiency of this conversion. According to obtain effectiveness we extract colour and texture features because of using a single feature extraction does not give high accuracy and effectiveness. High Dimensional feature reduce the query efficiency and low level feature reduce the query accuracy. So we have to integrate those above two visual features in our approach to obtain high effectiveness

2. RELATED WORK

Our proposed CBIR system is based on Dominant color and GLCM texture. But there is a focus on global features. Because Low level visual features of the images such as color, texture are especially useful to represent and to compare images automatically. In the concrete selection of color, texture description, we use dominant color, Gray-level co-occurrence matrix and Gradient vector flow field. The rest of the paper is organized as follows. The section 2.1 outlines existing color based methods and section 2.2 deals with existing texture based method and section 2.3 outlines the existing relevance feedback techniques. The section 3 presents our new proposed approaches. The section 4 shows the experimental results. The section 5 presents conclusions.

2.1. Existing Color System And Its Problem Statement

Color histogram is the most commonly used color representation, but it does not include any spatial information. Color correlogram describes the probability of finding color pairs at a fixed pixel distance and provides spatial information. Therefore color correlogram yields better retrieval accuracy in comparison to color histogram. Color autocorrelogram is a subset of color correlogram, which captures the spatial correlation between identical color only. Since it provides significant computational benefits over color correlogram, it is more suitable for image retrieval. DCD is MPEG-7 color descriptors. DCD describes the salient color distributions in an image or a region of interest, and provides an effective, compact, and intuitive representation of color presented in an image. However, DCD similarity matching does not fit human perception very well, and it will cause incorrect ranks for images with similar color distribution. Color quantization method for dominant color extraction, called the linear block algorithm (LBA), and it has been shown that LBA is efficient in color quantization and computation. For the purpose of effectively retrieving more similar images from the digital image databases, uses the color distributions, the mean value and the standard deviation, to represent the global characteristics of the image, and the image bitmap is used to represent the local characteristics of the image for increasing the accuracy of the retrieval system.

2.2. Existing Texture Based System with Its Problem Statement

Texture is also an important visual feature that refers to innate surface properties of an object and their relationship to the surrounding environment. Many objects in an image can be distinguished solely by their textures without any other information. There is no universal definition of texture. Texture may consist of some basic primitives, and may also describe the structural arrangement of a region and the relationship of the surrounding regions. The ability to retrieve images on the basis of texture similarity may not seem very useful-But the ability to match on texture similarity can often be useful in distinguishing between areas of images with similar color (such as sky and sea, or leaves and grass). A variety of techniques has been used for measuring texture similarity; the best-established rely on comparing values of what are known as second-order statistics calculated from query and stored images. Essentially, these calculate the relative brightness of selected pairs of pixels from each image. From these it is possible to calculate measures of image texture such as the degree of contrast**,** coarseness**,** homogeneity and regularity**,** or periodicity**,** correlation and entropy**.** Alternative methods of texture analysis for retrieval include the use of Gabor filters this is the widely used technique now a days. Texture queries/specifying can be formulated in a similar manner to color queries, by selecting examples of desired textures from a palette, or by supplying an example query image. The system then retrieves images with texture measures similar in value. A recent technique is the texture thesaurus, which retrieves textured regions in images on the basis of similarity to automatically-derived codeword's representing important classes of texture within the collection. In our approach we have used the texture features using gray-level co-occurrence matrix (GLCM).

2.3. Existing Relevance Feedback Technique Problems

The existing relevance feedback in content-based image retrieval is work as follows, First of all Machine provides initial retrieval results, through query-by-keyword, sketch, or example, etc then User provides judgment on the currently displayed images as to whether, and to what degree, they are relevant or irrelevant to her/his request; then the machine gets the feedback and tries again the searching process according to the feedback. If each image/region is represented by a point in a feature space, relevance feedback with only positive (i.e., relevant) examples can be cast as a density estimation or novelty detection problem; while with both positive and negative training examples it becomes a classification problem, or an on-line learning problem in a batch mode, but with the following characteristics associated with this specific application scenario:1.Smallsampleissue,2.Asymmetry in training sample,3.Real time Requirement. In Small sample issue the number of training examples is small (typically <20 per round of interaction) relative to the dimension of the feature space (from dozens to hundreds, or even more), while the number of classes is large for most real-world image databases. For such small sample size, some existing learning machines such as support vector machines (SVM) cannot give stable or meaningful results, unless more training samples can be elicited from the user. In

Asymmetry in training sample**,** the desired output of information retrieval is not necessarily a binary decision on each point as given by a classifier, but rather a rank- ordered top-k return. This is a less demanding task since the rank or configuration of the irrelevant classes/points is of no concerns long as they are well beyond the top-k returns. Most classification or learning algorithms, e.g.,discriminant analysis or SVM, treat the positive and negative examples interchangeably and assume that both sets represent the true distributions equally well However, in reality, the small number of negative examples is unlikely to be representative for all the irrelevant classes; thus, an asymmetric treatment may be necessary. In real time requirement finally, since the user is interacting with the machine in real time, the algorithm shall be sufficiently fast, and avoid if possible heavy computations over the whole dataset.

3. PROPOSED APPROACH

Only simple features of image information cannot get comprehensive description of image content. We consider the dominant color, texture features combining not only be able to express more image information, but also to describe image from the different aspects for more detailed information in order to obtain better search results. The proposed method is based on dominant color, texture features of image.

3.1. Color Feature Representation

In general, color is one of the most dominant and distinguishable low-level visual features in describing image. Many CBIR systems employ color to retrieve images, such as QBIC system and Visual SEEK. In theory, it will lead to minimum error by extracting color feature for retrieval using real color image directly, but the problem is that the computation cost and storage required will expand rapidly. So it goes against practical application. In fact, for a given color image, the number of actual color only occupies a small proportion of the total number of color in the whole color space, and further observation shows that some dominant color cover a majority of pixels. Consequently, it won't influence the understanding of image content though reducing the quality of image if we use this dominant color to represent image. Firstly, the RGB color space is uniformly divided into 8 coarse partitions, as shown in Fig. 2. If there are several color located on the same partitioned block, they are assumed to be similar. After the above coarse partition, the centroid of each partition (“color Bin” in MPEG-7) is selected as its quantized color.

Let I=(RI,GI,BI) represent color components of a pixel with color components Red, Green, and Blue, and Qi be the quantized color for partition i. The average value of color distribution for each partition centre can be calculated by,

$$I = \frac{\sum_{I \varepsilon Qi} I}{\sum_{I \varepsilon Qi} 1}$$

After the average values are obtained, each quantized color can be determined.

In this way, the dominant color of an image will be obtained.

3.2. Extraction of Texture of an Image

Most natural surfaces exhibit texture, which is an important low level visual feature. Texture recognition will therefore be a natural part of many computer vision systems. In this paper, we propose a texture representation for image retrieval based on GLCM. List may be presented with each item marked by bullets and numbers.GLCM is created in four directions with the distance between pixels as one. Texture features are extracted from the statistics of this matrix. Four GLCM texture features are commonly used which are given below: GLCM is composed of the probability value, it is defined by

P (i,j|d,θ) which expresses the probability of the couple pixels at θdirection and *d* interval. When θ and *d* is determined, P (i,j|d,θ) is showed by *Pi, j*. Distinctly GLCM is a symmetry matrix and its level is determined by the image gray-level. Elements in the matrix are computed by the equation shown below:

$$P(i, j|d,\theta) = \frac{P(i,j|d,\theta)}{\sum\sum P(i,j|d,\theta)}$$

GLCM expresses the texture feature according the correlation of the couple pixels gray-level value at different positions. It quantificational describes the texture feature. In this paper, four texture features are considered. They include energy, contrast, entropy, inverse difference.

$$\text{Energy } E=\sum_x \sum_y p(x,y)^\wedge 2$$

It is texture measures of gray-scale image represent homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture.

$$\text{Contrast } I=\sum\sum(x-y)^2 p(x,y)$$

Contrast is the main diagonal near the moment of inertia, which measures how the values of the matrix are distributed and number of images of local changes reflecting the image clarity and texture of shadow depth. Large Contrast represents deeper texture.

$$\text{Entropy}=\sum_x \sum_y p(x,y) log\ p(x,y)$$

Entropy measures randomness in the image texture. Entropy is minimum when the co-occurrence matrix for all values is equal. On the other hand, if the value of co-occurrence matrix is very uneven, its value is greater. Therefore, the maximum entropy implied by the image gray distribution is random. InverseDifference,

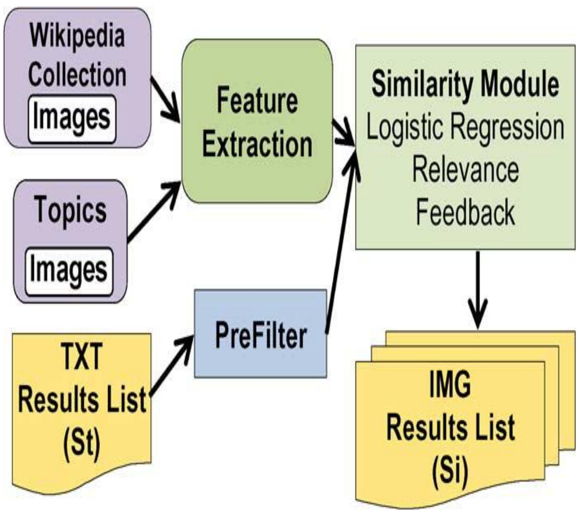
$$H=\sum_x \sum_y \frac{1}{1+(x-y)2} p(x,y)$$

It measures number of local changes in image texture. Its value in large is illustrated that image texture between the different regions of the lack of change and partial very evenly. Here $p(x, y)$ is the gray-level value at the Coordinate (x, y).The texture features are computed for an image when d=1 and ***=00, 450, 900, 1350***. In each direction four texture features are calculated. They are used as texture feature descriptor. Combined feature vector of Color and texture is formulated.

3.3. Computation of similarity

The similarity between query and target image is measured from two types of characteristic features which includes dominant color and texture features. Two types of characteristics of images represent different aspects of property. So during the Euclidean similarity measure, when necessary the appropriate weights to combine them are also considered. Therefore, in carrying out Euclidean similarity measure we should consider necessary appropriate weights to combine them. We construct the Euclidean calculation model as follows: D(A,B)=ω1D(FCA,FCB)+ω2D(FTA,FTB)

Here ω1 is the weight of color features, ω2 is the weight of texture features, *FCA* and *FCB* represents the 8 three dimensional color features for image A and B. For a method based on GLCM, *FTA* and *FTB* on behalf of 16 texture features correspond to image A and B. Here, we combine color texture features. The value of ω through experiments shows that at the



time ω1=0.4, ω2=0.3 has better retrieval performance

4. Experimental Results

The experiments were carried out on a Core i3; 2.4 GHz processor with 4GB RAM using MATLAB. The image database contains 100 kind of different image sets. Fig. 2 shows the image retrieval results using the proposed method with FFE. The image at the centre the query image and the other images are the retrieval results. The performance of a retrieval system can be measured in terms of its recall (or sensitivity) and precision (or specificity)**.** Recall measures the ability of the system to retrieve all models that are relevant, while precision measures the ability of the system to retrieve only models that are relevant. They are defined as

$$\text{Recall}=\frac{\text{Number of relevant images retrieved}}{\text{Total Number of relevant images}}$$

$$\text{Precision}=\frac{\text{Number of relevant images retrieved}}{\text{TotalNumberofrelevantimages}}$$

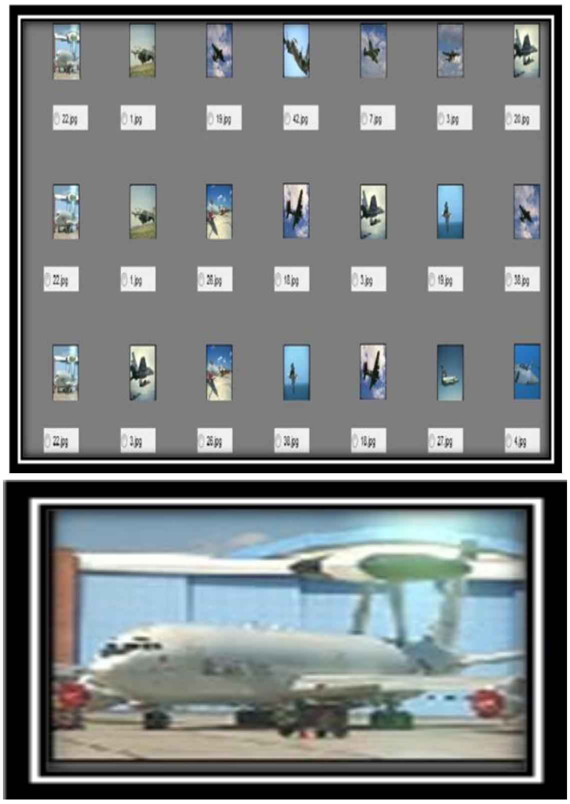


Fig1

5. Conclusion

In this paper, a CBIR method has been proposed which uses the combination of dominant color, GLCM texture. A total of 39 features covering color, texture proved that the proposed method yielded higher average precision and average recall. In addition, the proposed method almost always showed performance gain of average retrieval time over the other methods. As Further studies, the proposed retrieval method is to be evaluated for more various databases.

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