Content based Image Retrieval using Texture Contents

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Abstract: ***Textual information about images can be easily searched using existing technology, and it requires humans to manually describe each image in the database. This is impractical for very large databases or for images that are generated automatically. It is also possible to miss images that use different synonyms in their descriptions. CBIR is one of the most important and effective image retrieval methods used in different areas such as medical applications and being widely studied in both academia and industry.***

Keywords: CBIR, GLCM, Image Texture

1. Introduction

Content-based image retrieval (CBIR) is the application of computer vision techniques to the image retrieval problem i.e. searching for digital images in large databases for a recent scientific overview of the CBIR field. Content-based means that the search analyzes the contents of the image rather than the metadata such as keywords, tags, or descriptions associated with the image. The term "content" in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. CBIR is desirable because most web-based image search engines rely purely on metadata and this produces a lot of garbage in the results. Also having humans manually enter keywords for images in a large database can be inefficient, expensive and may not capture every keyword that describes the image. Thus a system that can filter images based on their content would provide better indexing and return more accurate results.

2. Related Works

Some work has been observed in CBIR system, which is based on a free hand sketch (Sketch based image retrieval – SBIR). It describes a possible solution how to design and implement a task, which can handle the informational gap between a sketch and a colored image, making an opportunity for the efficient search hereby. The used descriptor is constructed after such special sequence of preprocessing steps that the transformed full color image and the sketch can be compared [1].

The CBIR system uses a multitier 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 theory, are defined for multiple-image query and retrieval [2].

Image retrieval is one of the most exciting and fastest growing research areas in the field of multimedia technology. To evaluate the performance of the proposed algorithm, we assess the simulation's performance in terms of average precision and final score using several image databases, and perform comparative analysis with existing methods such as MPEG-7 [3].

The color feature is described by the CH, which is translation and rotation invariant. The Haar wavelet transformation is used to extract the texture features and the local characteristics of an image, to increase the accuracy of the retrieval system. The lifting scheme reduces the processing time to retrieve images. The experimental results indicate that the proposed technique outperforms the other schemes, in terms of the average precision, the average recall and the total average precision/recall [4].

One of the main aspects of color feature extraction is the choice of a color space. A color space is a multidimensional space in which the different dimensions represent the different components of color. An example of a color space is RGB, which assigns to each pixel a three element vector giving the color intensities of the three primary colors, red, green and blue. The space spanned by the R, G, and B values completely describes visible colors, which are represented as vectors in the 3D RGB color space. As a result, the RGB color space provides a useful starting point for representing color features of images. However, the RGB color space is not perceptually uniform. More specifically, equal distances in different intensity ranges and along different dimensions of the 3D RGB color space do not correspond to equal perception of color dissimilarity [5].

The given data base from where, the content based retrieval is to be implemented, the same feature vector is derived. And based on the comparison of the two vectors, images are retrieved.

In the propose work, we are considering all the parameters like color, texture, shape, entropy and wavelet HH sub band coefficients.

3. Image Retrieval based on Query Image Texture Contents

The texture based features are extracted from the database images and stored in a feature database. Similarly, the texture based features are extracted from the query image

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and the query image features are compared with the database image features using the distance measure. Images having the least distance with the query image are displayed as the result. Image Texture features are extracted using Gray Level Co-occurrence matrix (GLCM).

4. GLCM Matrix

The GLCM finds how often a pixel with a gray-level value i occurs either horizontally, vertically, or diagonally to adjacent pixels with the value j. It is given by the relative frequency of the occurrences of two gray-level pixels i & j, separated by d pixels in the θ orientation, where d is the displacement and θ is the direction. The 'd' can take values 1, 2, 3, etc., and θ can take values 0° (horizontal), 90° (vertical), 45° and 135°.

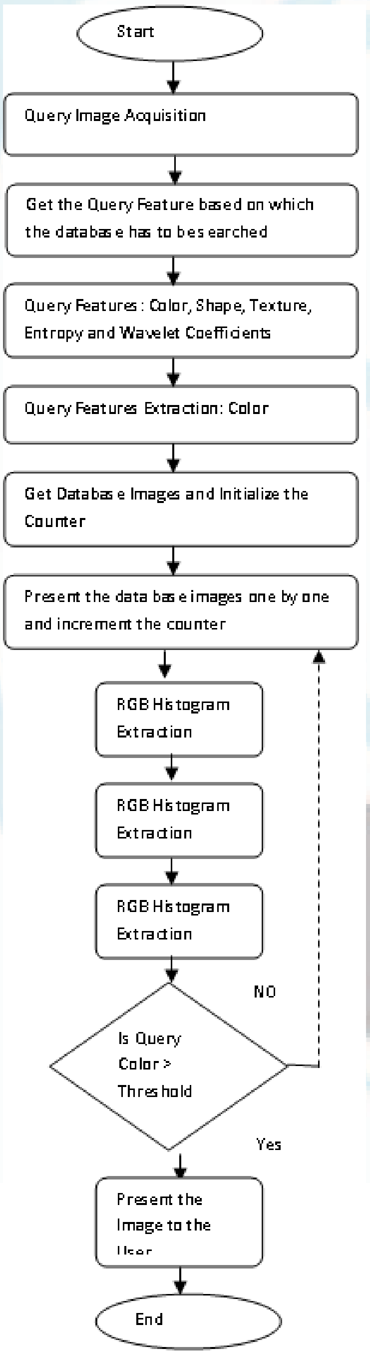

Figure 1: CBIR Flow diagram

5. GLCM Extraction

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. The number of gray levels in the image determines the size of the GLCM. The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset.

To create a GLCM, use the graycomatrix function. The graycomatrix function creates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right horizontally adjacent.

Spatial gray level co-occurrence estimates image properties related to second-order statistics. The use of gray level co-occurrence matrices (GLCM) have become one of the most well-known and widely used texture features. The GxG gray level co-occurrence matrix Pd for a displacement vector d = (dx, dy) is defined as follows. The entry (I, j) of Pd is the number of occurrences of the pair of gray levels i and j which are a distance d apart. Formally, it is given as;

$$P_{\mathbf{d}}(i,j) = \left|\{((r,s),(t,v)) : I(r,s) = i, I(t,v) = j\}\right|$$

After creating the GLCMs, image contrast, energy, correlation and homogeneity can be computed as follows:

Contrast → Measures the local variations in the gray-level co-occurrence matrix. Contrast is 0 for a constant image. The contrast is given by:

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 P_{\mathbf{d}}(i,j)$$

Correlation → Measures the joint probability occurrence of the specified pixel pairs. Correlation is 1 or -1 for a perfectly positively or negatively correlated image. Correlation is NaN for a constant image. The correlation is given by:

$$\text{Correlation} = \frac{\sum_i \sum_j (i-\mu_x)(j-\mu_y) P_{\mathbf{d}}(i,j)}{\sigma_x \sigma_y}$$

Energy → Provides the sum of squared elements in the GLCM, Also known as uniformity or the angular second moment. Energy is 1 for a constant image. The energy is given by:

$$\text{Energy} = \sum_i \sum_j P_d^2(i,j)$$

Homogeneity → Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity is 1 for a diagonal GLCM computation of entropy. Homogeneity is given by:

$$\text{Homogeneity} = \sum_i \sum_j \frac{P_d(i,j)}{1+|i-j|}$$

An important property of many textures is the repetitive nature of the placement of texture elements in the image. The autocorrelation function of an image can be used to assess the amount of regularity as well as the fineness/coarseness of the texture present in the image. Formally, the autocorrelation function of an image is defined as follows:

$$\rho(x,y) = \frac{\sum_{u=0}^{N} \sum_{v=0}^{N} I(u,v) I(u+x, v+y)}{\sum_{u=0}^{N} \sum_{v=0}^{N} I^2(u,v)}$$

Entropy

The expression of the information entropy of an image is given by:

$$H = -\sum_{i=0}^{L-1} p_i \ln p_i,$$

Where L denotes the number of gray level, pi equals the ratio between the number of pixels whose gray value equals i(0 i L _ 1) and the total pixel number contained in an image. The information entropy measures the richness of information in an image. If pi is the const for an arbitrary gray level, it can be proved that the entropy will reach its maximum.

6. Results and Conclusion

CBIR at present is still very much a research topic. The technology is exciting but immature, and few operational image archives have yet shown any serious interest in adoption. The crucial question that this report attempts to answer is whether CBIR will turn out to be a flash in the pan, or the wave of the future. Our view is that CBIR is here to stay. It is not as effective as some of its more ardent enthusiasts claim – but it is a lot better than many of its critics allow, and its capabilities are improving all the time. And as we argue in section **Error! Reference source not found.** Above, most current keyword-based image retrieval systems leave a great deal to be desired. In hard-nosed commercial terms, only one application of CBIR (video asset management) appears to be cost-effective – but few conventional image management systems could pass the test of commercial viability either.

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