Content Based Image Retrieval using Color and Texture Content

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Abstract - *This paper describes a hybrid feature extraction approach of our research and solution to the problem of designing a CBIR system manually. Two features are used for retrieving the images such as color and texture. Color feature is extracted by using different color space such as RGB, HSV and YCbCr. Texture feature is extracted by applying Gray Level Co-occurrence Matrix (GLCM). The image is retrieved by combining color and texture feature and the color space which gives the best result as analyzed using precision and recall graph.*

Keywords - *CBIR, GLCM, Image Texture, Color Spaces, Euclidean Distance, Image Retrieval, Precision, Recall.*

I. 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. It is a process of retrieving images from a database based on the features that are extracted from the images. Two types of features are present in the image ie., General and Domain Specific. General features or Low Level Features such as Color, Texture and Shape. Domain Specific or High Level Features such as emotions etc, these features are difficult to extract. The user provides a "query" image and the search is based upon that query. CBIR system is used in many applications such as Fingerprint Identification, Biodiversity Information Systems, Digital Libraries, Crime Prevention, Medicine, Historical Research, Trademark Image Registration, Automatic Face Recognition Systems, Fashion and Graphic Design, Architectural and Engineering Design, Remote sensing and Management of Earth Resources, Cultural Heritage, Publishing and Advertising etc. In the present work the experiments of CBIR have been used to evaluate the effect of different color space on model performance. 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. process of framework for efficiently retrieving images from a collection by similarity. The retrieval relies on extracting the appropriate characteristic quantities describing the desired contents of images. In addition, suitable querying, matching, indexing, and searching techniques are required.

II.RELATED WORK

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 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. The common ground for CBIR is to extract a signature for every image, based on its pixel values, and to define a rule for comparing images. The signature can be color, texture, shape or any other information with which two images could be compared. Distance metric or matching criteria is the main tool, for retrieving similar images from the large image databases, for all the above categories of search.

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. There are different methods for image retrieval using low level features color, texture and shape. In order to use good color space for specific application, color conversion is needed. In this paper color and texture features are used to retrieve the images. In color different color space are used, by converting the color images from RGB to another color spaces like Gray, HSV ,HSI, YCbCr ,Lab, CMY etc, and processing these images gives better results. In texture the co-occurrence matrix is used. 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.

III. IMAGE RETRIEVAL BASED ON QUERY IMAGE TEXTURE CONTENTS

Texture innate property of all surfaces, describes the visual patterns and that contain important information about the structural arrangement of the surface and its relationship to the surrounding environment. E.g. clouds, leaves, bricks, fabrics etc. It is a feature that describes the distinctive physical composition of a surface. In low level feature, texture co-occurrence matrix is used for retrieval of the images. 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 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).

A. GLCM Matrix

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 texture filter functions, described in Texture Analysis cannot provide information about shape, i.e., the spatial relationships of pixels in an image.)

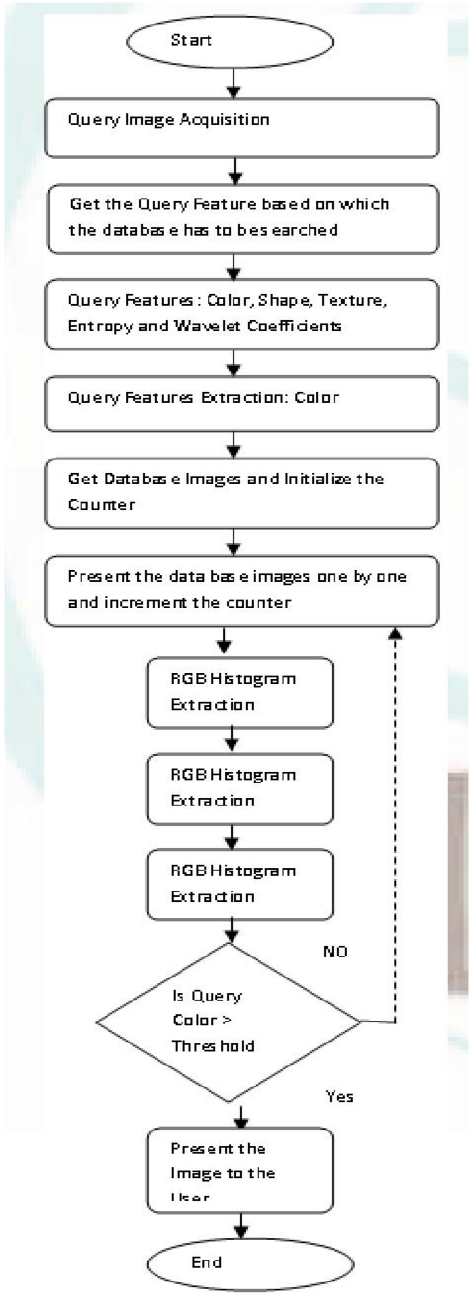


Fig 1: CBIR Flow diagram

B. GLCM Extraction

In machine learning, pattern recognition and in image processing , feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. When the input data to an algorithm. is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a features vector). This process is called *f*eature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

Feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to over fit to training samples and generalize poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.

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;

$$P_d(i,j) = |\{((r,s),(t,v)) : I(r,s) = i, I(t,v) = j\}|$$

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:

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

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:

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

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:

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

Co-Occurrence Matrix : While Calculating Co-Occurrence Matrix ,the image is first converted into gray scale , and the co-occurrence matrix is calculated called as Gray Level Co-Occurrence matrix (GLCM). Co-occurrence matrix describes spatial relationships between grey-levels in a texture image. GLCM is composed of the probability value, it is defined by p(i, j | d), which expresses the probability of the couple pixels at θ direction and d interval. When θ and d is determined, p(i, j | d), is showed by P i j, . Distinctly GLCM is a symmetry matrix; its level is determined by the image gray-level. Elements in the matrix are computed by using below equation

$$Y = 0.299R + 0.587G + 0.114B$$

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

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 auto correlation 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 : Entropy is the statistical measure of randomness. The expression of the information entropy of an image is given by:

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

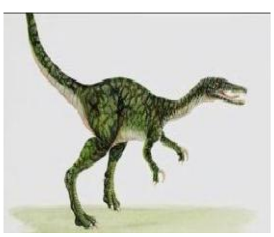
Where L denotes the number of gray level, pi equals the ratio between the number of pixels whose gray value equals i(0 i L _ 1) and the total pixel number contained in an image. The information entropy measures the richness of information in an image. If pi is the const for an arbitrary gray level, it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

IV. IMAGE RETRIEVAL BASED ON COLOR USING COLOR SPACES

Color Space is defined as model for representing colors in terms of intensity values. A color model is an abstract mathematical model describing the way colors can be represented as tuples of numbers, typically as three or four values of color components. Three different color space are used in this paper they are: RGB, HSV, YCbCr.

A. RGB Color Space

RGB is additive in nature. It is sum of three primary colors Red (R), Green (G) and Blue (B). The range of values of each of this components lies within 0 to 255. Any other color space can be obtained from a linear or non-linear transformation from RGB. It is one of most widely used color space for processing and storing the digital image data. However, high correlation between the red, green and blue colors. This color space is device dependent which means that the same signal or image can look different on different devices. In RGB chrominance and luminance component are mixed. The Figure 2 shows Top 10 retrieved images for RGB color space based on similarity distance using query image.



Query image

Fig 2: Top 10 Retrieved images for RGB colors space based on similarity comparison

B. HSV Color Space

HSV stands for Hue, Saturation and Value. Hue and Saturation defines chrominance, Value or intensity specifies luminance. Hue is used to distinguish colors, Saturation measures the percentage of white light added to the pure color, Value is the light intensity. The following equations show the transformation from RGB color space to HSV color space. Figure 3 shows the Top 10 retrieved images for HSV color space based on similarity distance using Query image.

$$h = \begin{cases} 0, \ if \max = \min \\ (60 \times \frac{g-b}{\max - \min} + 0^{0}) \bmod 360, \ if \max = r \\ 60 \times \frac{b-r}{\max - \min} + 120^{0}, \ if \max = g \\ 60 \times \frac{r-g}{\max - \min} + 240^{0}, \ if \max = b \end{cases}$$

$$s = \begin{cases} 0, \ if \max = 0 \\ \frac{\max - \min}{\max} = 1 - \frac{\min}{\max}, \ otherwise \end{cases}$$

v =max. Here, max represent the greatest of r, g, b and min represent the least.

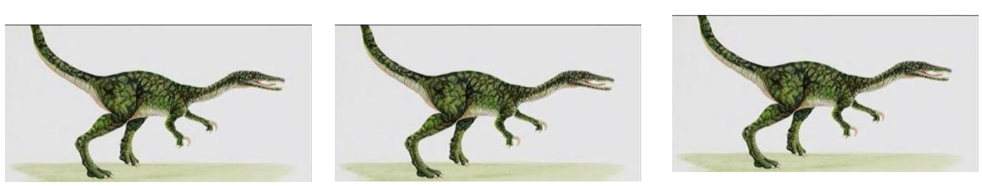


Fig 3: Top 10 retrieved images for HSV color space based on similarity distance.

Fig 4: Top 10 retrieved images for YCbCr colors space based on similarity distance.

C. YCbCr Color Space

YCbCr color space has been defined in response to increasing demands for digital algorithms. Y is luma component which represent the luminance and computed from nonlinear RGB . It is obtained as weighted sum of RGB values. Cb is difference between blue and luma component and Cr is the difference between red and luma component. The Y in YCbCr denotes the luminance component, and Cb and Cr represent the chrominance component. The following equations show the transformation from RGB to YCbCr color space.

Here, mean and standard deviation are calculated for every component in the set of chosen color spaces. Mean of pixels color depicts principal color of the image and standard deviation depicts the variation of pixel color.

Contrast gives the local variations in GLCM

$$\text{Contrast} = \sum\sum(\text{i} - \text{j})^2 P(\text{i}, \text{j})$$

$$Cr = R - Y$$

$$Cb = B$$

V. CONCLUSION

An image retrieval method using different color space and texture has been proposed.Experimental results showed that the precision and recall for buses, horses, and food image categories HSV color space gives good results than other color spaces. In future still more efficient color spaces and dintance measures can be applied to analyze the performance of color spaces.

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