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COLOR HISTOGRAM BASED MEDICAL IMAGE RETRIEVAL SYSTEM

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Abstract—This paper aims to focus on the feature extraction, selection and database creation of brain images for image retrieval which will aid for computer assisted diagnosis. The impact of content-based access to medical images is frequently reported but existing systems are designed for only a particular context of diagnosis. But, our concept of image retrieval in medical applications aims at a general structure for semantic content analysis that is suitable for numerous applications in case-based reasoning. By using the features, the database created for comparison. The color histogram is used to measure the similarity between the stored database image and the query image. The image which is more similar to the query image is retrieved as the resultant image. If the query image does not match with the stored database image, it will be considered as the new image to the database system.

Keywords— *Medical image, diagnosis, image retrieval, database, feature extraction, t-test.*

I. INTRODUCTION

In medical applications, processing of chest x-rays, cineangiograms, projection images of transaxonal tomography, and other medical images that occur in radiology, nuclear magnetic resonance, and ultrasonic scanning etc are being carried out. These images may be used for patient screening and monitoring or for detection of tumors or other diseases.

Radar and sonar images are used for detection and recognition of various types of targets or in guiding and maneuvering of aircrafts or missile systems. There are many more applications ranging from robot vision for industrial automation to image synthesis for cartoon making or fashion design. The term DIP generally refers to processing of a two dimensional picture by a digital computer. A digital image is an array of real or complex numbers presented by a finite number of bits. DIP is a technique of image manipulation using appropriate algorithms and mathematical tools. The steps involved in DIP are Image acquisition, Image manipulation, Pre-processing, Recognition and interpretation.

II. FEATURE EXTRACTION

2.1 Feature Extraction

Transforming the input data into the set of features is called feature extraction. Thus for a given medical image, the following types of features are extracted from each image:

1. First order statistics from the image histogram.
2. Second order statistics from the the co-occurance matrices.

First order features are the statistics calculated from the original image value. They do not consider pixel relationships. HSI features based on histogram from the first order feature. Second order statistics or the features consider the relationships between the groups of two pixels in the original image. Texture features are extracted using Gray Level Co-occurrence Matrices (GLCM) from second order features.

2.2 Color Feature Extraction Models

The extraction of the color features for each of the four methods is performed in the HSV (hue, saturation and value) perceptual color space, where Euclidean distance corresponds to the human visual system's notion of distance or similarity between colors.

2.2.1 The Conventional Color Histogram

The conventional color histogram(CCH) of an image indicates the frequency of occurrence of every color in the image. From a probabilistic perspective, it refers to the probability mass function of the image intensities. It captures the joint probabilities of the intensities of the color channels. The CCH can be represented as

$h_{A,B,C}(a,b,c) = N.Prob(A=a, B=b, C=c),$

Where A, B and C are the three color channels and N is the number of pixels in the image. Computationally, it is constructed by counting the number of pixels of each color (in the quantized color space).

2.2.2 The Fuzzy Color Histogram

In the fuzzy color histogram (FCH) approach, a pixel belongs to all histogram bins with different degrees of membership to each bin. More formally, given a color space with K color bins, the FCH of an image I is defined as $F(I)=[f_1,f_2,\ldots f_k]$ where

$$f_i = \frac{1}{N}\sum_{j=1}^{N}\mu_{ij}$$

Where N is the number of pixels in the image and μ_{ij} is the membership value of the j^{th} pixel to the i^{th} color bin, and it is given by

$$\mu_{ij} = \frac{1}{1 + d_{ij}/\varsigma}$$

Where d_{ij} is the Euclidean distance between the color of pixel j (a 3-dimensional vector of the H, S and V components), and the i^{th} color bin, and ς is the average distance between the colors in the quantized color space.

2.2.3 The Color Correlogram

The color correlogram (CC) expresses how the spatial correlation of pairs of colors changes with distance. A Color Correlogram for an image is defined as a table indexed by color pairs, where the d^{th} entry at location *(i,j)* is computed by counting number of pixels of color j at a distance d from a pixel of color i in the image, divided by the total number of pixels in the image.

2.2.4 The Color/Shape-Based Method

A color-shape based method (CSBM) in which a quantized color image *I'* is obtained from the original image *I* by quantizing pixel colors in the original image. A connected region having pixels of identical color is regarded as an object. The area of each object is encoded as the number of pixels in the object. Further, the shape of an object is characterized by 'perimeter intercepted lengths' (PILs), obtained by intercepting the object perimeter with eight line segments having eight different orientations and passing through the object center.

2.2.5 Algorithm for HSI Feature Extraction

The original 24-bit RGB images used in this study are of size M*N*3 were M and N are the height and width of image respectively and 3 indicates the three 8-bit RGB components of the original images, From the original image, RGB components are separated and the HSI components are derived. The mean, variance and range for all these 3 components (H, S and I) are calculated and a total of 9 HSI features (first order) are stored in HSI database. The database consists of simple flat files. The steps involved in HSI feature extraction are given in algorithm 2.1.

Algorithm 2.1: HSI feature Extraction

Input: Original 24-bit RGB Image
Output: 9 HSI features

Start
Step1: Separate the RGB components from the original 24-bit input color image.
Step2: Obtain the HSI components from the RGB components using the following equations.
Step3: Find the mean, variance and range for each RGB and HSI components.
Stop.

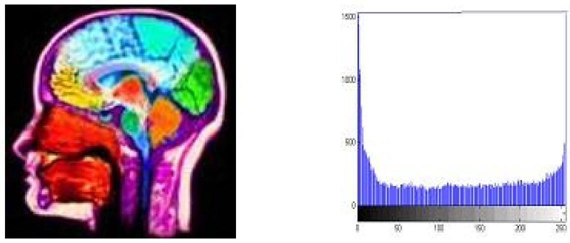


Figure 2.4 (a) Given medical image. (b) Histogram of given image

2.3 Texture Feature Extraction Models

The notion of texture generally refers to the presence of a spatial pattern that has some properties of homogeneity. Directional features are extracted to capture image texture information. The four texture feature extraction methods presented in this section generate a multi-scale, multi-directional representation of an image.

2.3.1 The Steerable Pyramid

The steerable pyramid recursively splits an image into a set of oriented sub-bands and a low pass residual. The image is decomposed into one decimated low pass sub-band and a set of undecimated directional sub-bands Statistical methods, including Fourier power spectra, co-occurrence matrices, shift-invariant principal component analysis (SPCA), Tamura feature, Wold decomposition, Markov random field, fractal model, and multi-resolution filtering techniques such as Gabor and wavelet transform, characterize texture by the statistical distribution of the image intensity.

2.3.2 The Contourlet Transform

The contourlet transform is a combination of a Laplacian pyramid (LP) and a directional filter bank (DFB). The LP provides the multi-scale decomposition, and the DFB provides the multi-directional decomposition. The LP is a decomposition of the original image into a wavelet Transform Features hierarchy of images, such that each level corresponds to a different band of image frequencies. This is done by taking the difference of the original image and the Gaussian low pass – filtered version of the image

2.3.3 The Complex Directional Filter Bank

The complex directional filter bank (CDFB) consists of a Laplacian pyramid and a pair of DFBs, designated as primal and dual filter banks. The filters of these filter banks are designed to have special phase functions, so that the overall filter is the Hilbert transform of the primal filter bank. A multi-resolution representation is obtained by reiterating the decomposition in the low pass branch

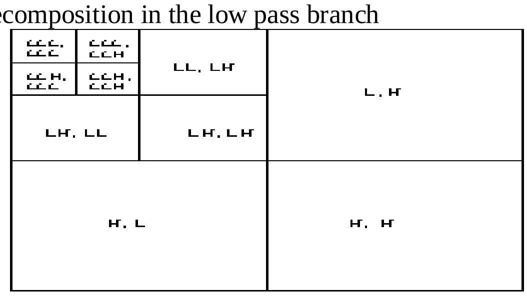


Figure 2.5. Pyramid Wavelet Transform (Level 3)

The standard Pyramid Wavelet Transform is shown in the Figure 2.5. The first step is to resize the image size into 256X256 in a matrix format. Then the pyramid wavelet transform is applied to get the sub bands of the image. To find the energy measures of the image Daubechies filter is applied. The decomposition is applied to 6 levels so that we can able to get the low frequency contents in the LL sub band and other frequencies in LH, HL and HH bands separately. Finally we will get the 4X4-sized image. Once the wavelet coefficients of an image are available, features are computed from each sub-band, resulting in 19 features for each image. The mean μ is the energy measure used to compute the features, and then the feature vector f, for a particular image is calculated as;

$f = [\mu_{mn}]$, $n \neq 1$ except for the coarsest level, $m=6$

$f = [\mu_{1,2}, \mu_{1,3}, \mu_{1,4}, \mu_{2,2}, \mu_{2,3} \ \dots \ \mu_{6,1}, \mu_{6,2}, \mu_{6,3}, \mu_{6,4}]$

Where μ_{mn} is the energy measure for the decomposition level and the sub bands. In this we get the energy coefficients and stored in the database.

Algorithm 2.2: Calculation of co-occurrence matrix $P_{f,d}(x,y)$ from the image $f(x,y)$

Input: Input gray level image f(x,y)**.**

Output: Co-occurrence matrix $P_{f,d}(x,y)$ for d=1 in the direction f.

Start

Step1: Assign $P_{f,d}(x,y) = 0$ for all x,y e[0,L] where L is maximum gray level.

Step2: For all pixels (x_1,y_1) in the image, determine (x_2,y_2) which is at distance d in direction f and perform

$P_{f,d}\,[f(x_1,y_1), f(x_2,y_2)] = P_{f,d}\,[f(x_1,y_1), f(x_2,y_2)] + 1$

Stop.

Algorithm 2.3: Textural feature extraction

Input: RGB components of original image**.**

Output: 24 Textural Features.

Start

Step1: Derive the Gray Level Co-occurrence Matrices (GLCM) Pf,d(x,y) for four different values of direction f (0^0, 45^0, 90^0, and 135^0) and d=1 which are dependent on direction f. (for simplicity d is taken to be 1)

Step2: Compute Co-occurrence Matrix which is dependent on direction using the Equation

$$C = \frac{1}{4}(P_0 0 + P_{45} 0 + P_{90} 0 + P_{135} 0)$$

Step3: For large height (M) and width (N) of the image, the relative frequency of co-Occurrences P(x,y) = C(x,y)/(M*N) represents approximately the joint probability mass of the discrete variables x,y. Henceforth the co-occurrences matrix be assumed to have the elements P(x,y) in place of C(x,y). Eight GLCM features namely mean variance, range, energy, entropy, contrast, inverse difference moment, correlation and homogeneity are calculated. Important measures based on texture are defined below.

$$\text{Mean } \mu = \sum_{x,y} xP(x,y)$$

$$\text{Variance } \sigma = \sum_{x,y} (x-\mu)^2 P(x,y)$$

Range = max2-min2

Where max2 = max (max1),

max1 = max(image), min2 = min(min1)

min1 = min(image)

Maximum probability = max(P(x,y))

$$\text{Energy} = \sum_{x,y} P^2(x,y)$$

$$\text{Contrast} = \sum_{x,y} |x-y|^k P(x,y)$$

$$\text{Inverse difference moment} = \sum_{x,y:x\neq y} \frac{P(x,y)}{|x-y|^k}$$

$$\text{Correlation} = \frac{\sum_{xy} [(xy)P(x,y)] - \mu_x \mu_y}{S_x S_y}$$

Where μ_x, μ_y, S_x, S_y are standard deviations defined by

$$\mu_x = \sum_x x \sum_y P(x,y)$$

$$\mu_y = \sum_y y \sum_x P(x,y)$$

$$S_x = \sum_x (x-\mu_x)^2 \sum_y P(x,y)$$

$$S_y = \sum_y (y-\mu_y)^2 \sum_x P(x,y)$$

Stop.

III. DESIGN METHODOLOGY FOR IMAGE RETRIEVAL

The architecture of proposed framework can be divided into two main subsystems namely, the enrollment and the query subsystem. The enrollment subsystem is responsible for acquiring the information that will be stored in the database for later use. On the other side, the query subsystem is responsible for retrieving similar images from the database according to the user's query image. The query subsystem receives an input query image from the user. For that purpose, a computation algorithm is used to speed up the retrieval process. Finally, the most similar database images are ranked and returned to the user.

Image retrieval is the process of finding similar images from a large image archive with the help of some key attributes associated with the images or features contained in the images. Here the input image is given by the user and it is preprocessed to get the feature extraction and feature selection values. The images given by the user and also the images in the database are compared to search for relevant images in the data base. The feature values extracted from this process are compared with the image feature values already stored in the database. If the database image feature values matched with the query feature values means, it displays the relevant images. Otherwise, the query image feature values are considered as the new image feature value and added to the database storage.

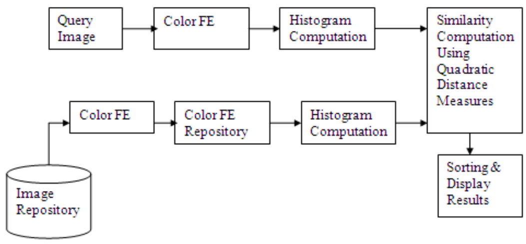


Figure 3.1 (a) Color Feature Extraction Block Diagram

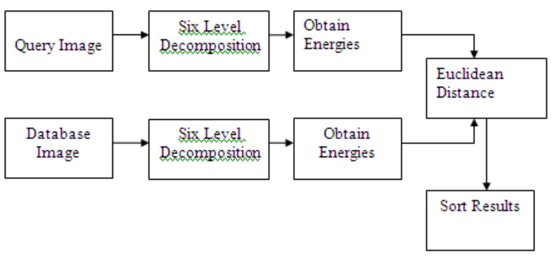


Figure 3.1(b) Texture Feature Extraction Block Diagram

The major statistical data that are extracted are histogram mean, standard deviation, and median for each color channel i.e. Red, Green, and Blue. So totally 3× 3 = 9 features per segment are obtained. All the segments need not be considered, but only segments that are dominant may be considered, because this would speed up the calculation and may not significantly affect the end result.

3.1 Color histogram definition

An image histogram refers to the probability mass function of the image intensities. This is extended for color images to capture the joint probabilities of the intensities of the three color channels. More formally, the color histogram is defined by,

$$h_{A,B,C}(a,b,c) = N \cdot \mathrm{Prob}(A = a, B = b, C = c)$$

Where A , B and C represent the three color channels (R,G,B or H,S,V) and N is the number of pixels in the image. Computationally, the color histogram is formed by discretizing the colors within an image and counting the number of pixels of each color. Since the typical computer represents color images with up to 224 colors, this process generally requires substantial quantization of the color space. The main issues regarding the use of color histograms for indexing involve the choice of color space and quantization of the color space. When a perceptually uniform color space is chosen uniform quantization may be appropriate. If a non-uniform color space is chosen, then non-uniform quantization may be needed. Often practical considerations, such as to be compatible with the workstation display, encourage the selections of uniform quantization and RGB color space. The color histogram can be thought of as a set of vectors. For gray-scale images these are two dimensional vectors. One dimension gives the value of the gray-level and the other the count of pixels at the gray-level. For color images the color histograms are composed of 4-D vectors.

3.2 Histogram Euclidean distance

Let **h** and **g** represent two color histograms. The Euclidean distance between the color histograms **h** and **g** can be computed as:

$$d^2(h,g) = \sum_A \sum_B \sum_C (h(a,b,c) - g(a,b,c))^2$$

In this distance formula, there is only comparison between the identical bins in the respective histograms. Two different bins may represent perceptually similar colors but are not compared crosswise. All bins contribute equally to the distance.

3.3 Histogram intersection distance

The color histogram intersection was proposed for color image retrieval in [4]. The intersection of histograms **h** and **g** is given by:

$$d(h,g) = \frac{\sum_A \sum_B \sum_C \min(h(a,b,c), g(a,b,c))}{\min(|h|,|g|)}$$

Where |**h**| and |**g**| gives the magnitude of each histogram, which is equal to the number of samples. Colors not present in the user's query image do not contribute to the intersection distance. This reduces the contribution of background colors. The sum is normalized by the histogram with fewest samples.

3.4 Histogram quadratic (cross) distance

The color histogram quadratic distance was used by the QBIC system. The cross distance formula is given by:

$$d(h,g) = (h-g)^t A (h-g)$$

The cross distance formula considers the cross-correlation between histogram bins based on the perceptual similarity of the colors represented by the bins. And the set of all cross-correlation values are represented by a matrix ***A***, which is called a similarity matrix. And a (*i*,*j*)th element in the similarity matrix ***A*** is given by : for RGB space,

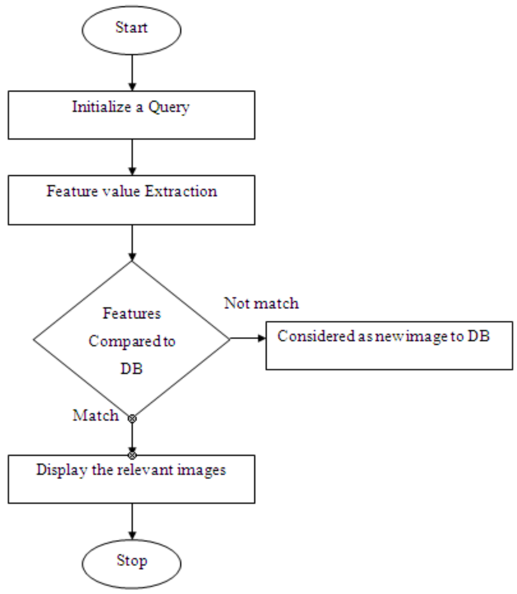
$$a_{ij} = 1 - d_{ij} / \max(d_{ij})$$

Where d_{ij} is the distance between the color *i* and *j* in the RGB space. In the case that quantization of the color space is not perceptually uniform the cross term contributes to the perceptual distance between color bins.

For HSV space it is given by:

$$a_{ij} = 1 - \frac{1}{\sqrt{5}}[(v_i - v_j)^2 + (s_i \cos h_i - s_j \cos h_j)^2 + (s_i \cos h_i - s_j c$$

which corresponds to the proximity in the HSV color space.



IV. RESULTS AND DISCUSSIONS

The general flow of the experiments starts with the decomposition of data base image using Haar, D4 wavelets and Haar, D4 Lifting procedure in offline. The maximal decomposition level J = 4. The repeated decomposition is used for query image. The features are extracted from the image to form feature vector and performed highly efficient image matching. The progressive retrieval strategy is used to balance between computational complexity and retrieval accuracy. The main focus is on the comparison of two important retrieval indices, namely retrieval accuracy and the speed. The test image database contains over 100 medical images of 24 bits true color. In this all images are pre processed to 256x256 sizes before decomposition. Sample data base images for each category are shown below. The retrieval accuracy is defined as the ratio between the number of relevant images (belongs to the same category) retrieved and the total number of retrieved images (known as a single precision)

$$\text{Retrieval Accuracy} = \frac{\text{Number of relevant images}}{\text{Total number of images retrieved}}$$

In the literature survey for various CBIR methods, the semantic gap between low level features and high level concept is more and the retrieved output consisted lot of errors. Hence the proposed method retrieves the images based on color, texture and metadata features. The integrated results will be outputted to the user hence the retrieval accuracy will be high and less interaction is needed. The proximity between two images is calculated using two different techniques: Euclidian distance between color histograms and ED between wavelet energies.

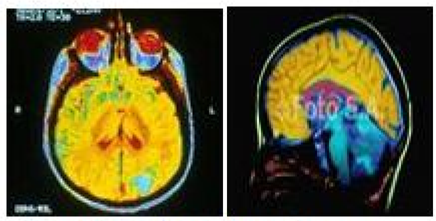


Figure 4.1(a) Query image

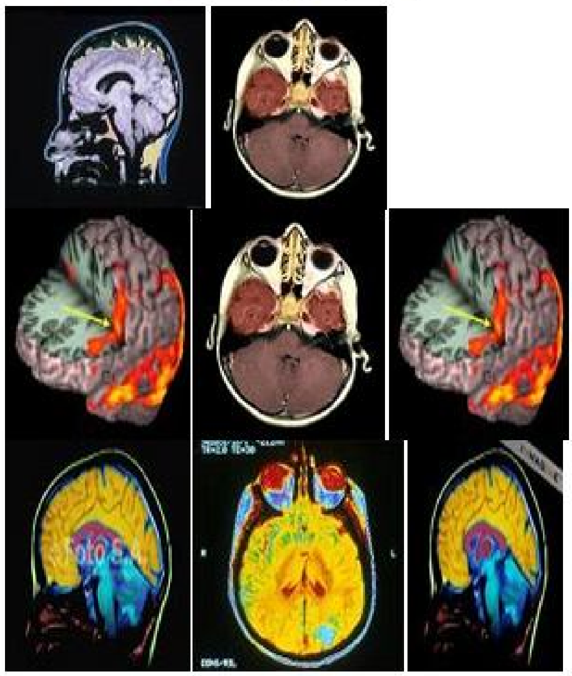


Figure 4.1 (b).Retrieved mages from Database

The below images show RGB plane separation and its corresponding Histograms.

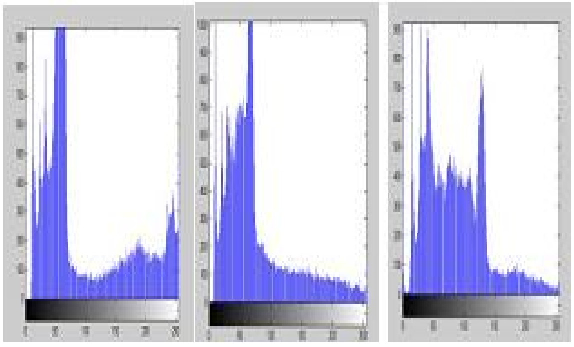


Fig 4.2 Histogram for RED Plane Histogram for GREEN Plane Histogram for BLUE Plane

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