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A REVIEW OF LOW LEVEL VISUAL FEATURES FORA CONTENT BASED MEDICAL IMAGE RETRIEVAL SYSTEM

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ABSTRACT

Medical imaging is a precious and essential tool in healthcare systems, helps the physicians to emanate good quality of treatment. The advancement in medical Technology has resulted in a huge number of medical images which are stored in a database for future purpose. It is very imperative to build an effective retrieval system which browse through entire database in diagnosing the various diseases, helping the therapeutic process and in supporting the medical decision makingprocess. Content based Image Retrieval (CBIR) assists in retrieving the required medical images from a huge database on the basis of their visual features like shape, color and texture. Medical images are generally represented in gray level rather than color. Feature extraction plays an important role in an ever-increasing the performance of the medical image retrieval system. This paper presents a various multiple feature extraction techniques for effective content based medical image retrieval system.

Keywords: content based image retrieval, texture features, shape features.

INTRODUCTION

It has been revolutionized every sector of activity including medical field. In the medical field medical experts and diagnosis experts, researchers make use of several medical images for their applications. The number of medical images in the database has been increasing day to day. These medical images are essential in diagnosing the different diseases and curing process and in supporting the medical decision making process Muller H in [1] has described the importance of image retrieval clinical benefits and he has given various directions for future purpose. Moniresh and Esnashari described the importance of image retrieval in retrieving the images related to eye disease [2]. T Glataed explained the application of image retrieval in cardiac imaging in [3]. Ashish applied these image retrieval techniques for retrieving dental and skull images also [4].

Basically, there are two methods for searching required medical images. They are concept based searching method and content based searching method Peter Wilkins explains the text based approaches for content based image retrieval system in [5]. Yong Rui and Thomas have given indetail explanation of image retrieval and its future directions [6].The text based technique confronted with many challenges because of its complex nature. It is cumbersome to save database images which involve large manual annotations, consumption of too much time and huge expenses. The more the number of database images are the more complex problems will be. Since there are innumerable images in a given database, even a medical expert has to struggle to retrieve required images which facilitate the diagnosing process in time and it is very difficult to describe medical images with a text. To address these limitations, content-based image retrieval (CBIR) approaches have been researched in the last decade. Content based methodology answers the problems involved in the text based methodology Xiang-yang wang in [7] and Rajshree in [8] presents a novel retrieval framework for combining color, texture and shape information which improves the performance of the retrieval system.

Content Based Image Retrieval (CBIR), is a dynamic research area facilitates the process of retrieving the required medical images from the large data base on the basis of their visual low level features like shape, color and texture. Ashwani has discussed the importance of texture features based image retrieval in [9].The effectiveness of the content based medical image retrieval system (CBMIR) powerfully depends on the selection of the set of visual features. These features plays important role in CBMIR System. The images required medical images can be retrieved by the medical expert by providing the query image whose content is similar to that of retrieved images. Feature extraction plays a major role in CBMIR system. Most of the medical images are gray in nature so we are concentrating on the texture and shape features. Multiple features enhances the performance of the retrieval system. Young Deok explained the effectiveness of multiple features in CBMIR in [10].

Medical images are mainly in gray scale, for diagnosing gray scale images texture and shape feature are extracted. A feature is defined to conveys certain visual properties of an image, either or locally for a small region of the pixels or globally for the complete image. The

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contents of an image described with the help of their features the content of the image can be described more efficiently by employing multiple features rather than single feature. They combine the advantages of individual features resulting in a better retrieval system.

Medical image retrieval system

The architecture of the basic Content based medical image retrieval system illustrated in Figure-1 consist of three phases and discussed as fallows.

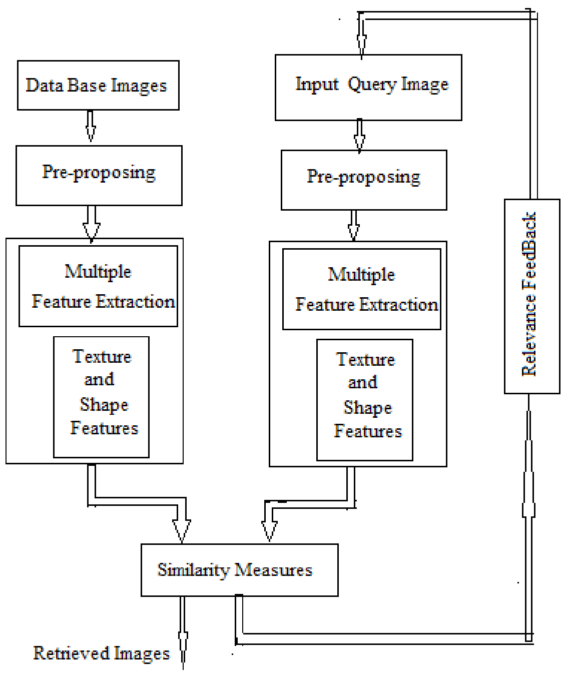

Figure-1. Architecture of the basic content bases medical image retrieval system.

The classic conceptual content-based medical retrieval system consists of three phases: off-line feature extraction phase, online image retrievalphase and feedback phase.

In offline phase, the images stored in the database are pre-processed for reducing noise with the help of median filter. Latter, the visual content of the image is described by adapting multiple features.These extracted feature componentsare stored in the database along with the images. The database consists of a variety of classes of medical images of certain human organs such as liver, lungs brain etc. The same feature extraction process fallowed for query image in online image retrieval phase.

In online phase the query image is submitted as an input to the retrieval system for searching similar images. The system retrieves the relevant images by computing the similarity matching between the feature vectors of the query image and those of the data base images. Finally, the system returns the results which are most relevant to the query image.

In most of the cases the user may not satisfy with the initial result then feedback process is used to modify the query image. In feedback phase user interacts with the system to modify query image representations. It is the process of selecting the most relevant image for searching again and using the information feuded back by the user about the relevance of previously retrieved images such that the adjusted query is a better approximation to the user's information.

Texture feature extraction methods

Texture is characterized by the spatial distribution of gray levels in a neighborhood. Thus, texture cannot be defined for a point. The resolution at which an image is observed determines the scale at which the texture is perceived. texture as repeating patterns of local variations in image intensity which are too fine to be distinguished as separate objects at the observed resolution. Thus, a connected set of pixels satisfying a given gray-level property which occur repeatedly in an image region constitutes a textured region

A feature is used to describe the content of an image, either or locally for a small group of pixels region or globally for the entire image. The input image F(i, j) where i, j are the pixel coordinates in the image.

Medical images have particular textural patterns. These patterns have specific information.Medical images are regularly represented in gray level, most medical image surfaces exhibit texture cannot describe only for a point. Texture is a natural surface property and it has repetitive pixel information about the structural arrangement and it also gives the relationship between the surface and external surroundings. Basavara explained the importance of texture features in [11].Basically there are two types of texture extraction methods namely statistic texture feature extraction method and structural texture feature extraction method. The statistic texture features using gray-level co-occurrence matrix (GLCM), Markov random field (MRF) model, etc. Han et al. [12] proposed a rotation-invariant and scale-invariant Gabor representations, Gabor features, have been particularly successful in many computer vision and image processing applications. Gabor features are among the top performers in face recognition and fingerprint matching [13-14]

Statistical texture analysis

Texture is a spatial property, since sstatistical methods extensively used in classification of texture and particularly when the texture patterns are very small.

First-order statistics

These features correspond to the average grey level, standard deviation, entropy, skewness and kurtosis.

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Second-order statistical features

In order to capture the spatial dependence of gray-level values which contribute to the perception of texture, a two-dimensional dependence matrix known as a gray-level co-occurrence matrix is extensively used in texture analysis. Gray-level co-occurrence matrix (GLCM) corresponds to the Second-order statistical features whichdescribes the special distributionof the gray levels with the surrounding regions. The following steps give the detailed description of the mathematical calculation of the statistical component analysis.

Angular Second Moment (ASM): This static is also called as Energy and it measures the textural uniformity that is pixel pair repetitions. It detects disorders in textures. Energy reaches a maximum value equal to one. High energy values occur when the gray level distribution has a constant or periodic form. Energy has a normalized range. The GLCM of less homogeneous image will have large number of small entries

$$ASM = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\{F(i,j)\}^2 \qquad (1)$$

.

Contrast (C): This statistic measures the spatial frequency of an image and is difference moment of GLCM. It is the difference between the highest and the lowest values of a contiguous set of pixels. It measures the amount of local variations present in the image. A low contrast image presents GLCM concentration term around the principal diagonal and features low spatial frequencies.

$$C = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left|x-y\right|F(i,j)\,(2) \qquad (2)$$

Variance (V): This statistic is a measure of heterogeneity and is strongly correlated to first order statistical variable such as standard deviation. Variance increases when the gray level values differ from their mean

$$V = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(x-\mu)^2 F(i,j) \qquad (3)$$

Correlation (Cr): The correlation feature is a measure of gray tone linear dependencies in the image.

$$Cr = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\frac{\{xXy\}X(F(i,j)-\{\mu_i X\mu_j\})}{\sigma_i X\sigma_j} \qquad (4)$$

Homogeneity (H): This statistic is also called as Inverse Difference Moment (IDM). It measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements. It is more sensitive to the presence of near diagonal elements in the GLCM. It has maximum value when all elements in the image are same. GLCM contrast and homogeneity are strongly, but inversely, correlated in terms of equivalent distribution in the pixel pairs population. It means homogeneity decreases if contrast increases while energy is kept constant.

$$IDM = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\frac{1}{1+(x-y)^2}F(i,j) \qquad (5)$$

Entropy (E): A feature which measures the randomness of gray-level distribution is the entropy, which is defined as

$$E = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}F(i,j)X\log(F(i,j)) \qquad (6)$$

Correlation (Cr): Auto correlation function exhibits periodic behavior with a period equal to the spacing between adjacent texture primitives. When the texture is coarse, the autocorrelation function drops off slowly, whereas for fine textures it drops off rapidly. The autocorrelation function is used as a measure of periodicity of texture as well as a measure of the scale of the texture primitives.

$$Cr = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\frac{\{xXy\}X(F(i,j)-\{\mu_i X\mu_j\})}{\sigma_i X\sigma_j} \qquad (7)$$

Histogram features

Histograms are one of the basic spatial domain processing techniques. It can be used to provide helpful image statistics; such as image compression, contrast enhancement and segmentation.Histogram features of images give the probability of occurrenceof gray levels in an image.The histogram itself is not sufficient for describing the structural arrangement of an image. But a simple one-dimensional histogram is not useful in characterizing texture. The drawback of this is explained with an example. If an image in which pixels alternate from black to white in a checkerboard fashion will have the same histogram as an image in which the top half is black and the bottom half is white.

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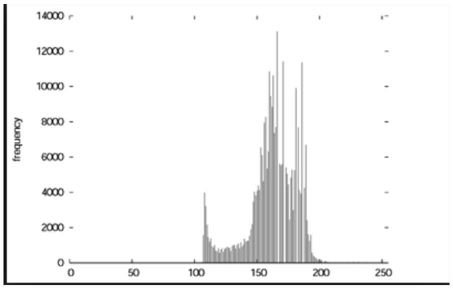

Figure-2. Sample histogram of an image.

This graph showing that the number of pixels in an image at various intensity value found in corresponding image. This method can be extended to extract the edges present in an image using edge histogram descriptors.

Edge Histogram Descriptor (EHD)

The edge histogram descriptor used for the spatial distribution of five types of edge in local image regions, which are defined as four directional edges and non-directional edge discussed by Wong et al in [15]. The four directional edges are generated by counting edges at 0^o, 45^o, 90^o and 135^o directions respectively. In the implementation of the descriptor, an image is divided into 4 X 4 non-overlapping sub-images. Further, each sub-image is divided into image blocks. The five types of edge information can be extracted from the image blocks by edge detection operators. Thus, for each sub-image a local edge histogram with 5 bins is generated and the total of 80 histogram bins (16 sub-images multiplying 5 bins) is achieved for the whole images. The division of sub-image and image block is illustrated in Figure-3.

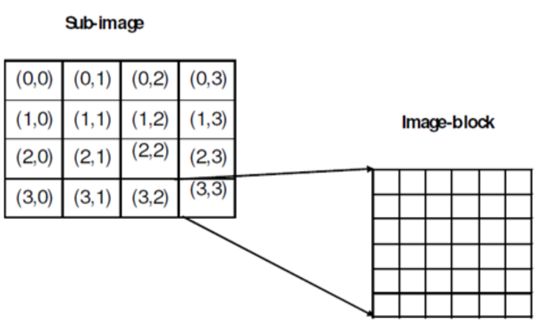

Figure-3. Edge Histogram descriptor in blovk image.

Here an image-block is denoted as B and the edge filter (2 X 2 matrix) coefficients are denoted as f(k), k= 0,1,2,3. The magnitude m of each edge can be calculated as follows

$$m = \left| \sum_{k=0}^{3} BXf(k) \right| \qquad (8)$$

If the maximum value among the five types of edge strength is greater than a Pre-determined threshold, the image-block is considered as containing the corresponding edge in it. Otherwise, the image-block contains no edge. After all edge values of the same type are summed up in one sub-image, the five bins for different edge types are obtained for each sub-image. The values of the edge bins are normalized by the total number of blocks. The retrieval can be performed based on the extracted Edge Histogram texture descriptor features in the image retrieval system.

Gabor features: The Gabor filter based feature extraction is the 2D Gabor filter function defined in [16] as follows.

$$\psi(x,y) = \frac{f^2}{\pi\gamma\eta} e^{-(\frac{f^2}{\gamma^2}x'^2 + \frac{f^2}{\eta^2}y'^2)} e^{j2\pi f x'} \qquad (9)$$

$$x' = x\cos\theta + y\sin\theta \;,\; y' = -x\sin\theta + y\cos\theta$$

In the spatial domain (Equation (8)) the Gabor filter is a complex plane wave multiplied by an origin-centred Gaussian filter. f is the central frequency of the filter ,θ the rotation angle. In the given form, the aspect ratio of the Gaussian is $\frac{\eta}{\lambda}$. This function as the following analytical form in the frequency domain is given as

$$\psi(x,y) = e^{-\frac{\pi^2}{f^2}(\gamma^2(u'=f)^2 + \eta^2 v'^2)}$$

$$u' = u\cos\theta + v\sin\theta \;,\; v' = -u\sin\theta + v\cos\theta \qquad (10)$$

Local binary pattern: In this approach the image is divided into a grid of small of non overlapping regions, where a histogram of the LBP for each region is constructed discussed by Y. Rodriguez in [17]. The LBP feature vector, in its simplest form, is created in the following manner:

Initially pre-process the image to remove the noise for further processing. Divide the examined window into cells (e.g. 16x16 or 8x8 pixels for each cell). For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise. Where the center pixel's value is greater than the neighbor's value, write 1, otherwise, write 0. This gives an 8-digit binary number.

- Compute the histogram, over the cell, of the frequency of each number occurring and each combination of which pixels are smaller and which are greater than the center. Optionally normalize the histogram. Concatenate (normalized) histograms of all cells. This gives the feature vector for the window.

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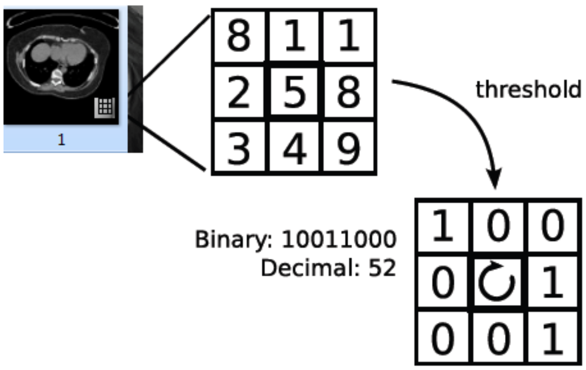

Figure-4. LBP operator.

Local line binary pattern

The inspiration of Local Line Binary Pattern (LLBP) is based on Local Binary Pattern (LBP) which is an improvement of LBP operator. It is a popular method already applied in image/face representation, classification and texture analysis. The basic difference of LLBP, LBP are as follows. Its neighbourhood covers a straight line with length N pixel. The allocation of binary mass is happening from the left to right adjoining pixel of middle pixel to the end of left and right side. The algorithm procedure of LLBP is defined as follows. First, allocate the binary code all along with horizontal and vertical route which characterizes the alteration in image strength respectively.

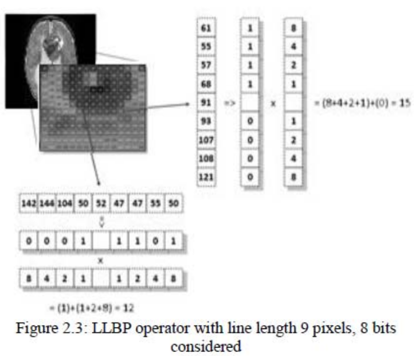

Figure-5. LLBP operator with line length 9 pixels, 8 bits considered.

Structural texture analysis

Structural methods which describe the primitives and their placement rules are useful. For example, consider a simple texture formed by the repeated placement of homogeneous gray-level discs in a regular grid pattern. Structural methods extensively used in classification of textureand particularly when the texture patterns are very large.Such patterns can be characterized by segmenting with the help of morphological operations.

Such a texture can be described by first segmenting the discs using a simple method such as connected component labeling, described earlier, and then determining the regular structure formed by the centroids of these connected components. For more general binary images the primitives can be first extracted using morphological methods and then their placement rules determined. Such morphological methods are particularly useful when the image is corrupted by noise or other non repeating random patterns which would be difficult to separate in a simple connected component method.

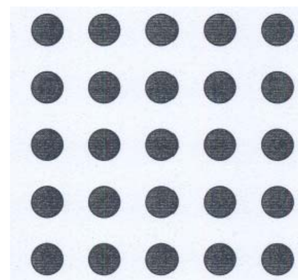

Figure-6. A simple texture pattern.

Model-based methods for texture analysis

An approach to characterize texture is to determine an analytical model of the textured image being analyzed. Such models have a set of parameters. The values of these parameters determine the properties of the texture, which may be synthesized by applying the model. The challenge in texture analysis is to estimate these model parameters so that the synthesized texture is visually similar to the texture being analyzed. Markov random fields (MRFs) have been studied extensively as a model for texture. In the discrete Gauss-Markov random field model, the gray level at any pixel is modeled as a linear combination of gray levels of its neighbors plus an additive noise term as given by the following equation:

$$F[i,j] = \sum_{[k,l]} F[i-k, j-l]h[k,l] + n[i,j] \tag{11}$$

When patterns forming texture have the property of self-similarity at different scales, fractal-based models may be used. A set is said to have the property of self-similarity if it can be decomposed as a non overlapping union of N copies of itself scaled down by a factor r. Such a texture is characterized by its fractal dimension D, given by the equation

$$D = \frac{\log N}{\log(\frac{1}{l})} \tag{12}$$

The fractal dimension is a useful feature for texture characterization. Estimation of D from an image is rather difficult because natural textures do not strictly follow the deterministic repetitive model of fractals assumed above but have statistical variations.

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Shape feature extraction methods

Shape features can also provide useful information for identifying entities. Because humans can recognize objects solely from their shapes. Usually, the shape carries semantic information Wei Zhang explained the shape based image retrieval techniques in [16].Basically; there are two shape feature extraction methods boundary-based and region-based. The former extracts the boundary information of an object. It does not provide any information about the interior region. The frequently used Shape representation methods include curvature scale space (CSS) described by Basavaraj in [18], Fourier descriptors given by Raj bhuvan yadav in [19], polygonal approximation, Deformable templates and]. The latter extracts the features based on the entire region. The various region based methods discussed are in the following sections. Among the region based descriptors, moments play a significant role and are very popular as they help in identifying most similar shapes from the database by taking into account the fine details.

Curvature scale space (CSS)

CSS is one of the well known global and contour based shape descriptor technique. The main benefit of this method is that it is robust to noise, scale and orientation changes. It is mostly used in object recognition, content based image retrieval (CBIR), shape similarity retrieval etc.

Steps involved in CSS

a) The contour of the image is obtained by using canny edge detector then convolved with the Gaussian kernel this process is called as smoothing of the image curve is known asσ1. The convolution consist of two parameters such as u is called arc length parameter and 'scale parameter. σ 'is gradually increased during convolution and the image get smoothed as 'σ2. The scale parameter 'increases. The CSS image consists of several arch shaped contours which depend on the object. The evolution of the CSS curve stops when the number of curvature zero crossings become zero.

Fourier descriptors

In general, a shape signature is any 1-D function representing 2-D areas or boundariesshape. Let the coordinates of the boundary of an image is $C(t) = \{(x(t), y(t)), t = 0, 1, \ldots N-1\}$ as shown in Figure-7. Theshape signature of the boundary points is computed usingcentroid distance function as given in Equation (3).

$$r(t) = [(x(n) - x_c)^2 + (y(n) - y_c)^2]^{\frac{1}{2}} \tag{13}$$

$$x_c = \frac{1}{N}\sum_{n=0}^{N-1} x(n), y_c = \frac{1}{N}\sum_{n=0}^{N-1} y(n)$$

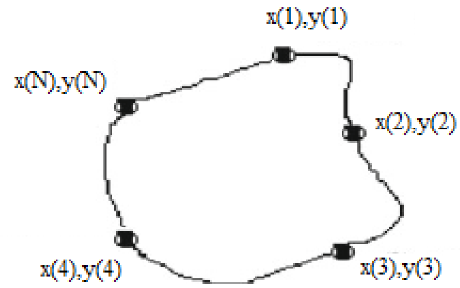

Figure-7. Simple of fouried descriptor.

$$a_n = \frac{1}{N}\sum_{k=0}^{N-1} c(t)\exp^{-j2\pi k/N} \tag{14}$$

The shape of the medical image is represented with the feature vector consisting ofFourier coefficients s as given below:

$$FS= [A, FD1, FD2,\ldots FDN-1]. \tag{15}$$

The first coefficient of the FD is called Dc component and it is ignored to make shape representation invariant to the boundary starting point.

Region based shape descriptors

To eliminate the problems associated with the continuous orthogonal moments, Hue and Mukundan has suggested the use of discrete orthogonal moments in [20]-[22]. Moments of images provide efficient local descriptors and have been used extensively in image analysis applications. Their main advantage is their ability to provide invariant measures of shape. They showed that Chebyshev moments are superior to geometric, Zernike, and Legendre moments in terms of image reconstruction capability. In this section we present a brief overview of the Chebyshev moments. For a digital image $f(x, y)$ with size $N\times N$, and $(n+m)^{th}$ order.

Invariant moments (IM)

In the past decades, various moment functions due to their abilities to represent the image features have been proposed for describing images.Hue first derived a set of moment invariants, which are position, size and orientation independent. These moment invariants have been successfully used in the field of pattern recognition. The general form of a moment function of order (p+q), of an image function f(x,y) is given as

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Where $\psi_{pq}$is known as the moment weighting kernel or the basis set.,for a digital image f(x,y) the above equation can be rewritten in discrete form as

$$M_{pq} = \sum_x \sum_y \Psi_{pq}(x,y) f(x,y). \quad (16)$$

Geometric moments are the simplest of the moment functions with basis $\psi_{pq}= x^p y^q$while basis set is not orthogonal.

A set of 7 invariant moments (IM) which are invariant to rotation, scaling and translation are given by the following equation:

$$\begin{aligned}
&\phi_1 = \eta_{20} + \eta_{02}.\\
&\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2.\\
&\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2.\\
&3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03}) +\\
&[3(\eta_{30} + \eta_{12})^2 + (\eta_{21} - \eta_{03})^2].\\
&\phi_6 = (\eta_{20} + \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] +\\
&4\eta_{11}^2(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}).\\
&\phi_7 = (3\eta_{11} - \eta_{03}) + (\eta_{30} + \eta_{12}) + [(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2]\\
&+(3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2].
\end{aligned} \quad (17)$$

IM are computationally simple. These moments suffer from a high degree of information redundancy, Noise sensitivity; Higher-order moments are very sensitive to noise.

Zernike moments (ZM)

To overcome the problems associated with the and invariant moments Teague has suggested the use of continuous orthogonal moments in [23].He introduced continuous-orthogonal Zernike moments and Legendre moments based on the orthogonal Zernike and Legendre polynomials,. Several studies have shown the superiority of Zernike moments over Legendre moments due to their better feature representation we choose Zernike moments as our second shape descriptor. Zernike polynomials are a complete set of complex valued functions orthogonal over the unit disk, i.e., $x^2 + y^2 \le 1$.

$$V_{nm}(x,y) = V_{nm} = (r\cos\theta, r\sin\theta,) = R_{nm}(r) = \exp(jm\theta) \quad (18)$$

Where $R_{nm}(r)$ is the orthogonal radial polynomial.

$$R_{nm}(r) = \sum_{s=0}^{(n=|m|)/2} (-1)^s \frac{(n-s)!}{s!x\left[\frac{n-2s-|m|}{2}\right]!\left[\frac{n-2s-|m|}{2}\right]!} r^{n-2s}$$

$n = 0,1,2....;\ 0 \le |m| \le |n|\ ;\ n - |m|$ is even

The Zernike moment of order n with repetition m of a continuous function $f(x, y)$ is given by

$$Z_{nm} = \frac{n+1}{\pi} \int_x \int_y f(x,y) V^*_{nm}(x,y)\,dxdy, x^2 + y^2 \le 1. \quad (19)$$

For a digital image $f(x, y)$, above equation can b approximated as

$$Z_{nm} = \frac{n+1}{\pi} \sum_x \sum_y f(x,y) V^*_{nm}(x,y), x^2 + y^2 \le 1. \quad (20)$$

$$Z_{nm} = \frac{n+1}{\pi} \sum_r \sum_\theta f(r\cos\theta, r\sin\theta) R_{nm}(r) \exp(jm\theta), \quad r \le 1. \quad (21)$$

The magnitudes of Zernike moments are invariant to rotation and they are robust tonoise. Since the basis is orthogonal, they have minimum information redundancy. However, the computation of ZM (in general, continuous orthogonal moments) poses several problems.

Legendre Moments (LM)

Moments with Legendre polynomials as kernel function, denoted as Legendre moments, were first introduced by Srinivasa Rao [24]. Legendre moments are orthogonal moments which are used to attain a near zero value of redundancy measure in a set of moment functions, so that the moments correspond to independent characteristics of the image. The two-dimensional Legendre moments of order (p+q), with image intensity function f(x,y) are defined as follows.

$$L_{pq} = \frac{(2p+1)(2q+1)}{4} \int_{-1}^{1} \int_{-1}^{1} P_p(x) P_q(y) f(x,y)\,dxdy. \quad (22)$$

where Legendre polynomial ($P_p(x)$ of order p is given by

$$P_p(x) = \sum_{k=0}^{p} \left\{ (-1)^{\frac{p-k}{2}} \frac{1}{2^p} \frac{(p+k)!x^k}{\left(\frac{p-k}{2}\right)!\left(\frac{p+k}{2}\right)!k!} \right\}_{p-k=even} \quad (23)$$

The recurrence relation of Legendre polynomials, ($P_p(x)$ is given as follows

$$P_p(x) = \frac{(2p-1)xP_{p-1}(x) - (p-1)P_{p-2}(x)}{p} \quad (24)$$

Tchebichef moments (TM)

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Mukundan *et al*. [25, 26] has suggested the use of discrete orthogonal moments to eliminate the problems associated with the continuous orthogonal moments. They introduced Chebyshev moments based on the discrete orthogonal Chebyshev polynomial. They showed that Chebyshev moments are superior to geometric, Zernike moments in terms of image reconstruction capability. Recently, Mukundan [26] introduced Chebyshev moments which possess rotational invariance property. In this section we present a brief overview of the Chebyshev moments. For an image of size $N \times N$ are defined according to the following recursive relation. For a digital image $f(x, y)$ with size $N\times N$, The scaled orthogonal Chebyshev polynomials of $(n+m)^{th}$ order is given as

$$t_0(x) = 1.; t_1(x) = (2x - N + 1)/N. \quad (20)$$

$$t_p(x) = \frac{(2p-1)t_1(x)t_{p-1}(x) - (p-1)\{1 - \frac{(p-1)^2}{N^2}\}t_{p-2}(x)}{p}. \quad (25)$$

$$P(p,N) = \frac{N\left[1-\frac{1}{N^2}\right]\left[1-\frac{2^2}{N^2}\right]\cdots\cdots\cdots\left[1-\frac{p^2}{N^2}\right]}{2p+1}. \quad (26)$$

$$S_{pq} = \frac{1}{2\pi\rho(P,m)} \sum_{r=0}^{m-1} \sum_{\theta=0}^{2\pi} t_p(r) e^{-j2\theta} f(r,\theta). \quad (23)$$

CONCLUSIONS

Feature extraction is a significant task in efficient medical image retrieval. This paper presents a various approaches for effective content based medical image retrieval based on texture and shape feature analysis. The combination of these features gives the superior result in improving the performance of the retrieval system. In addition various classifiers and feedback mechanisms can be integrated with the feature extraction method to enhance the efficiency of content based medical image retrieval system. Thus CBMIR System will be an effective tool in assisting CAD System to assist the radiology in medical domain. This will greatly aid diagnosis and research purposes.

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