



Wavelet Based Texture Analysis for Medical Images

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ABSTRACT: Texture analysis is quite important operation in medical image processing. Wavelet based texture analysis is developed which gives better way of extracting inherent object and properties in medical image. It gives a robust technique in disease diagnosis and future of biophysical disorder ness in a body. Image processing has an important influence on the medical decision making process and even on surgical actions. In this paper the importance of texture analysis of medical images with Wavelets are discussed and its application.

KEYWORDS: Texture analysis, Medical Images, Wavelets..

I. INTRODUCTION

Medical imaging is one of our most powerful tool for gaining insight into normal and pathological processes that effect health. The role of image processing in medicine is expanding with the increasing importance of finding ways to improve workflow in reading environments where more images are being acquired in more acquisition modalities, a variety of texture features based on image histogram, co-occurrence, run-length and gradient matrices[1], autoregressive model [2] and wavelet transform [3] can be computed.

Image processing playing a crucial role in the maturation of quantitative imaging techniques, such as in functional MRI and diffusion tensor MRI, where visualization of the acquired images alone is insufficient. Image processing, embedded in larger systems and applications, is used more and more extensively in medicine from diagnosis to therapy. Image processing has an important influence on the medical decision making process and even on surgical actions. Therefore, high quality and accuracy are expected. Texture analysis such as segmentation, classification and multiresolution plays vital role in computer vision and pattern recognition and is widely applied to many areas such as vision, Robotics, biomedical image processing and remote a sensing. Analysis of texture requires the identification of proper attributes or feature that differentiate the textures In the image after segmentation, classification and recognition. According to the methods employed to evaluate the inter-relationships of the pixels, the forms of texture analyses are categorized as structural, model-based, statistical and transform methods [4]. The performance of the image processing methods may have an important impact on the performance of the larger systems as well as on human observer that needs to analyze all of the available image data and render a diagnostic or therapeutic decision. An emerging focus is the development of imaging biomarkers for drug or therapy response, and the development and application of sophisticated image analysis methods in order to improve the accuracy of diagnosis, or to better predict outcomes of diseases or treatment and intervention strategies.

II. RELATED WORKS

Approaches to texture analysis are usually categorised into

- Structural,
- Statistical,
- Model-based and
- Transform methods.

Structural approaches [11] represent texture by well defined primitives (microtexture) and a hierarchy of spatial arrangements (macrotexture) of those primitives. To describe the texture, one must define the primitives and the placement rules. The choice of a primitive (from a set of primitives) and the probability of the chosen primitive to be



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placed at a particular location can be a function of location or the primitives near the location. The advantage of the structural approach is that it provides a good symbolic description of the image; however, this feature is more useful for synthesis than analysis tasks.

Statistical approaches do not attempt to understand explicitly the hierarchical structure of the texture. Instead, they represent the texture indirectly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image. Methods based on second-order statistics (i.e. statistics given by pairs of pixels) have been shown to achieve higher discrimination rates than the power spectrum (transform-based) and structural methods [12].

Model based texture analysis [13], using fractal and stochastic models, attempt to interpret an image texture by use of, respectively, generative image model and stochastic model. The parameters of the model are estimated and then used for image analysis.

Transform methods of texture analysis, such as Fourier [14] and wavelet transforms [15] represent an image in a space whose co-ordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size). Methods based on the Fourier transform perform poorly in practice, due to its lack of spatial localisation.

III. WAVELETS

A wavelet is a basis function that is isolated with respect to time or spatial location and frequency or wave number. Each wavelet has a characteristic location and scale. It thus has a location where it maximizes, a characteristic oscillation period, and also a scale over which it amplifies and declines. Two fundamental types of wavelets can be considered, the Grossmann-Morlet time-scale wavelets and the Gabor-Malvar time-frequency wavelets. The more commonly used type in geophysics is probably the time-scale wavelet. These wavelets form bases in which a signal can be decomposed into a wide range of scales, in what is called a "multiresolution analysis"[5]. Wavelets represent a technique that analyzes the frequency content of an image within different scales of that image. This analysis yields a set of wavelet coefficients corresponding to different scales and to different frequency directions.

Wavelets can be used in signal analysis, image processing and data compression.

Now a days wavelets are a tool of choice for engineers, physicists, and mathematicians, leading to efficient solutions in time and space frequency analysis as well as a multitude of another applications.

IV. WAVELET TRANSFORM

The wavelet transform is a multiresolution technique, Wavelet transforms are broadly divided into three classes: continuous, discrete and multiresolutional based the Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required.. There are various Wavelet transforms like Haar ,Daubechies, Coiflets, Symlet and etc. Wavelet transforms [6]represent an image in a space whose co-ordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size). The wavelet uses subband coding to selectively extract different subbands from the given image. These subbands can then be quantized with different quantizers to achieve good compression. specifically designed wavelet filters are used to satisfy certain constraints called the smoothness constraints[5]. The original image is subdivided into four parts. The LL band contains low frequency contents of the signal, where as HH band contains high frequency contents of the signal, which is having less importance than LL band., Under these constraints an efficient real-space implementation of the transform using quadrature mirror lters exists [8].

V. TEXTURE ANALYSIS

Texture analysis such as segmentation, classification and multiresolution plays vital role in computer vision and pattern recognition and is widely applied to many areas such as vision, Robotics, biomedical image processing and remote a sensing. Analysis of texture requires the identification of proper attributes or feature that differentiate the textures In the image after segmentation, classification and recognition. There are various forms of texture analyses are categorized as structural, model-based, statistical and transform methods.

The accurate defect detection and decomposition of texture into different levels is one of the most fundamental problems in computer vision and medical image inspection. We must be able to recognize and label homogeneous texture regions, proper dimensions and spacing within an image and differentiate the irregularities. Texture analysis is based on similarities in their contents [9], i.e., textures, colors, shapes, etc., which are considered the lower



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(An ISO 3297: 2007 Certified Organization)

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level features of an image. The above problem is most important and fundamental tasks of early vision. The solution to many vision related problems depend on an efficient image segmentation, decomposition and multiresolution. Thus the development of accurate texture description models, a linear symmetric phase filtering to remove noise without losing texture information and optimal detection of boundaries between nonhomogeneous texture regions.

The computational processing of texture can be divided into three main problem areas, segmentation, classification and multiresolution. Texture classification consists of taking whole images and grouping them into texture classes or categories, so as to be able to rapidly detect whether two texture samples are alike or dissimilar. Texture segmentation is, on the other hand, the process by which an image is partitioned into regions of homogeneous texture patterns. Segmentation is most a more complex problem than classification since it involves discriminating textures and being able to tell them apart. Every spectral component is not resolved equally as was the case in the Short time Fourier transform (STFT). In STFT the time and frequency resolutions are determined by the width of the analysis window, which is selected once for the entire analysis, i.e. both time (space) and frequency resolutions are constant. Therefore it is difficult to detect abruptness, nonhomogeneity and missing of component from weave accurately. It also have problem in optimal detection of boundaries along the dimension of yarn with hairiness and phase asymmetry between warp and weft along with pattern surface variation of patterns and texture distribution. The frequency event changes sharply along and across weaving direction.

VI. WAVELETS AND FILTER FUNCTION

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale [7]. Different wavelets Such as Morlet, Mexican hat, Meyer, Haar, Daubechies, Symlets, Coiflets, Splines biorthogonal investigated by different persons having different applications.

The usefulness of transformations is that they project a functions onto a new set of basic functions. If one or more basic functions represent a feature, and all the other basis functions are orthogonal to it, then one can quickly determine if a feature exists in a signal by projecting then signal function onto the new basis. An image is information prescribed by the statistical values assigned to points in space and how these values are distributed spatially. The textural feature indicates the characteristics contained in the over-all relationship that the gray levels in the image have to one another. The Two Dimensional wavelet Transform to the image can distinguish texture feature along with yarn spacing in the weave. The information obtained from the image processing is considered to be significant for purposes of textile design to obtain a basic knowledge as to the visual information contained therein.

Daubechies proposes modifications of her wavelet such that their symmetry can be increased while retaining simplicity. Symlet wavelet is used to extract the feature from the enhanced image. Symlet wavelet is a family of wavelets. It is a modified version of Daubechies wavelet with increased symmetry. Symlet is a quasisymmetric extension of the Daubechies wavelet. The properties of two wavelets are similar. There are 7 different functions from sym2 to sym8. Symlets are compactly supported wavelets having minimum asymmetry and highest number of vanishing moments for a given support width. Symmetric filters are linear phase filters. More precisely, a filter with filter coefficients a_n is

$$a(\xi) = \sum_n a_n e^{-in\xi}$$

called linear phase if the phase of the function $\arg a(\xi)$ is a linear function of ξ , i.e., if for some $l \in \mathbb{Z}$, $a(\xi) = e^{-il\xi} |a(\xi)|$. This means that a_n are symmetric around l , $a_n = a_{2l-n}$.

The phase introduced by I. Daubechies for Symlet wavelet is given below

$$\widehat{\Phi}^1(\xi) = m_0(\xi/2) \overline{m_0(\xi/4)} m_0(\xi/8) \overline{m_0(\xi/16)} \dots$$

$$= \prod_{j=1}^{\infty} [m_0(2^{-2j-1}\xi) \overline{m_0(2^{-2j-2}\xi)}]$$

where



International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2015

$$m_0(\xi) = \frac{1}{\sqrt{2}} \sum_n h_n e^{-in\xi}$$

The phase $\widehat{\Phi}^1$ of the Symlet wavelet is closer to linear phase than that of dbN,

$$\widehat{\Phi}(\xi) = \prod_{j=1}^{\infty} m_0(2^{-j} \xi)$$

The continuous wavelet transform decomposes a function $f(x)$ at several scales. With the help of special function Ψ called mother wavelet decomposition is achieved by convolving the function with the dilations and translations.

Where mother wavelet:

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(x) \Psi * \left(\frac{x-b}{a}\right) dx, a \in R^+, b \in R \quad (1)$$

The function $f(x)$ can then be recovered as

$$f(x) = \frac{1}{C^\Psi} \int_{-\infty}^{\infty} W(a,b) \Psi\left(\frac{x-b}{a}\right) \frac{dad b}{a^2}, \quad (2)$$

where, C^Ψ is a constant depending only on Ψ .

The discrete version of this transform results from the sampling of the parameter space (a, b) . One of the most well known discrete wavelet transform algorithm is multi-resolution analysis.

We can see the initial discrete signal $C_0(k)$ as the projections of $f(x)$ on V_0 ,

$$C_0(k) = \langle f(x), \Phi(x-k) \rangle = \int_{-\infty}^{\infty} f(x) \Phi(x-k) dx. \quad (3)$$

The projection on a subspace V_i ,

$$C_i(k) = \left\langle f(x), \frac{1}{2^i} \Phi\left(\frac{x}{2} - k\right) \right\rangle,$$

Is then an approximation of C_0 at scale or resolution i . The greater i , the coarser the approximation will be. For scaling function fulfilling certain conditions, the difference between two successive approximations C_{i-1} and C_i is a discrete signal [10].

VII. RESULT AND DISCUSSION

Co-occurrence matrix based features

Co-occurrence matrix, the second-order histogram, is a square matrix with $N_g \times N_g$ dimensions; N_g is a number of image gray levels. The co-occurrence matrix element $h_{k,l}$ is defined as

$$h_{k,l} = \sum_{\substack{x,y \in ROI \\ x+p,y+q \in ROI}} \left\{ \begin{array}{l} 1 \text{ if } (i_{x,y} = k \wedge i_{x+p,y+q} = l) \\ 0 \text{ elsewhere} \end{array} \right\} + \sum_{\substack{x,y \in ROI \\ x+p,y+q \in ROI}} \left\{ \begin{array}{l} 1 \text{ if } (i_{x,y} = l \wedge i_{x+p,y+q} = k) \\ 0 \text{ elsewhere} \end{array} \right\}$$

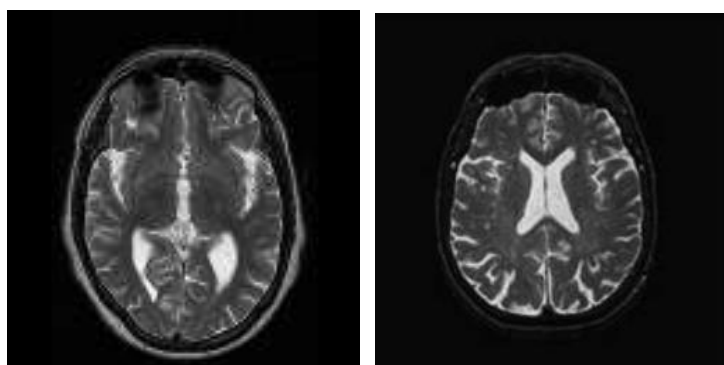
There are 11 features computed for a chosen parameters p and q . Definitions of these features can be found in [11].

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(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2015

The MRI Brain is used to describe texture analysis where normal and abnormal brain MRI is Taken shown in fig.1.



a: Abnormal brain

b: Normal brain

Fig .1 Normal and Abnormal Images

Build up a 4×4 features form the previous co-occurrence matrices as shown in Table1. There are various features used for texture analysis, some of them are shown in the Table1.

Table 1. Four Main Features used in Feature Extraction

Feature	Formula
Energy	$\sum_i \sum_j P^2(i, j)$
Entropy	$\sum_i \sum_j P(i, j) \log P(i, j)$
Contrast	$\sum_i \sum_j (i - j)^2 P(i, j)$
Homogeneity	$\sum_i \sum_j \frac{P(i, j)}{1 + i - j }$

Wavelet-based features

The discrete wavelet transform (DWT) for images is a linear operation that transforms 2n×2n image matrix (n is positive integer value) into a matrix of the same dimensions. The transposed input image is multiplied by transform matrix; the result is transposed and multiplied once again by the same transform matrix. Half of transform matrix rows may be considered as smoothing filter (L) coefficients, while the other as sharpening filter (H) coefficients. Hence, the obtained matrix consists of four square quarters (marked as LL, HL, LH and HH and called sub-bands). The Energy feature is computed for each subband. Thus, the total number of feature values based on the wavelet transform may differ according to input image dimensions.

$$Energy = M^{-1} \sum_{x,y \in ROI} i_{x,y}^2$$

where the parameter $i_{x,y}$ is a resulting matrix element. Summation is performed for every pixel (x,y) located in the defined ROI and M is a total number of these pixels.

VIII. APPLICATIONS

Texture analysis is very important study for medical images. The various applications are:

1. To explore medical images from diagnosis to therapy.
2. Removal of Noise from Medical Images.
3. To Verify / Identify Fingerprints.



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Vol. 4, Issue 5, May 2015

4. Segmentation of the structure can be done, based on the texture characteristics of the structure.
5. Texture analysis is most important for those cases in which change cannot be detected by direct inspection of the image.
6. Complexity of Medical Images are not understandable by visual inspection of the image of the tissue. So, they can be demonstrated by statistical analysis of the pixel distribution in the image of the structure.

Most applications described above have been performed on all types of medical images because of the great amount of detail provided by this technique. Texture analysis is useful not only in medicine. Application of such analysis to agriculture and food processing industry leads to fruitful results.

IX. CONCLUSION

We have described here the Wavelets and Wavelet transforms, and texture analysis of medical images using wavelets. Texture analysis is based on similarities in their contents i.e., textures, colors, shapes, etc., which are considered the lower level features of an image. Texture parameters are simply a mathematical representation of image features that can be characterized in words as smooth, rough, grainy and so on. It is an effective method for future improvement in the quality of medical images. Filter functions are very important to understand the texture analysis and feature extraction techniques. Techniques of texture features computation described here are quite well known.

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