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Texture Feature Extraction Methods and Wavelet Standpoint

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ABSTRACT: Image content based features analysis is the emerging area of research in medical imaging and in large databases. Texture is one of the important characteristics used for the analysis of medical images and interest regions in the image. With the development in the technology and image processing algorithms like wavelet based multi-resolution analysis and Gabor filter methods provided the platform to extract the texture features in an effective way. This paper aims at describing different approaches currently used for image based retrieval and feature extraction.Texture feature extraction maps the spatial structural patterns either stochastic or geometric in differences of gray level in the image. Different texture measures are presented and analyzed with categorization. Later wavelet based method has been chosen and the statistical features has been extracted with parameters such as mean and standard deviation.

KEYWORDS: Feature extraction; Discrete wavelet transforms; gray level difference; Textures; Gabor filter

I. INTRODUCTION

An image consists of different texture regions, and the features in these images can be used for search and retrieval. The Gabor representation of the image is optimal in minimizing the joint two-dimensional uncertainty in space and frequency. Texture is hidden complex patterns composed of different entities, which has different properties like color, brightness, uniformity, structure and shape. Below is the list of different texture measures used for the feature extraction of images,

DIFFERENT TEXTURE MEASURES

A. **Gray-level difference method** – Gray level difference method based on finding the differences between the gray level and average gray level between different neighbouring pixels. It calculates the probability distribution function of the image. There are four components which are extracted with this method, DIFFX and DIFFY shows the histograms of gray-level differences between neighbouring pixels. DIFF2 component shows the absolute differences while DIFF4 in all principle directions which represents the texture measures of the image.

B. **Center-symmetric covariance measures** – Initial studies showed that the texture features are the loaded features that are distributed over symmetric patterns. So for measuring the gray-level antisymmetric texture feature as well the computation of local auto-covariance or correlation of centersymmetric pixel values are computed. The non-uniform distribution of gray level can be better analysed with this method.

C. **Local binary patterns -** Texture patterns are introduced which was used to characterize the texture image. Eight elementsare used to represent the texture unit (TU). Each of which has the three possible values (0,1,2) that is calculated from the neighbourhood three pixels. There more than 5000 texture units in a 3 x 3 neighbourhood, the distribution of such a pattern over a region is called texture spectrum.

D. **Complementary feature pair -** In many cases, one texture feature is not sufficient to describe the complete set of features so in that case different features can be combined to obtain the complementary feature pair which provide the better way to understand the image features. Shen and Bie combined the parameters gradient magnitude and direction, gray level and direction jointly to define the texture features. Other features can also be combined to find the complementary features like entropy, size, energy, pixel count etc.

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The Texture feature extraction algorithms are usually categorized into different categories like,

A. **Structural-** In this approach, the texture is represented by primitive patterns also called micro textures with spatial arrangements called macro features on the top of it. For defining the texture, primitives and placement rules must be defined. Structural approach is advantageous in terms of representation of the image symbols. And the features extracted are more useful for reconstruction of the image. There may be issues with the definition of the image at micro and macro level. Structural extraction method provides a better platform for analysing image such as bone and detecting changes in structure of body.

B. **Statistical -** Statistical approach is based on the representation of texture indirectly and by distribution of certain parameters like grey levels and relationships among them. Second order statistics is having higher discrimination rates than transform rates. Second order pixel discrimination shows better representation than transform based methods. The representation of textures in gray level images is spotted easily with second order pixel discrimination method. co-occurrence matrix is the most powerful second-order statistical features for texture based feature analysis.

C. **Model Based -** Model based feature extraction methods uses fractal and stochastic models to represent the texture features of the image. The image analysis is done using the parameters found in the models. For modelling natural textures, fractal based model is useful. However for local image structures it is not so good. Different model are in use today for the feature extraction like AR model, Gaussian model, Gibbs RMF model. The AR model assumes a local interaction between the image pixels.

D. **Transform Based -** Transform based texture extraction methods such as Gabor and wavelet transform represents an image in time, frequency and space domain which has the direct mapping with the co-ordinate system useful to find the texture features. Fourier transform is good for frequency localization but space localization reduces with frequency. There is a compromise between these two. Gabor filter shows better results in terms of spatial localization but reconstruction is difficult as single filter resolution is difficult. Wavelet transforms is much advantageous in such case because it better represents the image both spatial and frequency grounds. There is wide range of wavelets available which can be opted for better performance. Below section shows Transform based feature extraction like Gabor filter and wavelet based feature extraction method.

II. RELATED WORK

Feature extraction using operators such as “texture energy measures” calculated by Laws in [2]. The convolution of filter mask with the image is done and statistics like mean variance are computed for all pixel in the filtered image. Laws’ filter functions have much similarity with Gabor filter. Conners, Harlow and Trivedi in [3] derived texture parameters with spatial gray level dependence method[5] from co-occurrence matrices. Different measures like inertia, energy, entropy, cluster province etc. taken for each matrix.

Dinstein et al. [6] proposed the fast discrimination between textured and uniform regions using simple operator. In this method the K*K window is taken and gray level difference between highest and lowest is calculated and assigned to the centre pixel which forms the output image. The value determines the textured level in the image. In another method [7] the set of simple masks applied like vertical, horizontal, diagonal and anti-diagonal rather than edge-like masks described in Laws [2]. Granlund proposed an unsupervised texture segmentation operator based technique [8]. The operator measures the magnitude and direction of gray scale image. Texture feature extraction is achieved by applying the operator to the transformed image.Wermser and Lissel[9] compared the Granlind’d with Abele[10] method and Chen and Palidis[11] method. The presence of noise introduced difficulties in image quality.

Knutsson and Granlund[12] introduced more sophisticated operators. In [13], Dondes and Rosenfeld propose a pixel classification scheme based on mean gray level classification. Using pyramid structure, Lee [14] proposed the technique to predict the texture regions in an image. It assumes that by performing averaging the pyramid will change to uniform region. Lowitz proposed histogram extracted features for segmenting the textures.Xu and Fu[15] proposed the segmentation of image using transforms, in this, gray level is reduced using multiple thresholding and then

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segmentation is performed using algorithms like co-occurrence matrices and split and merge. In [17] Jernigan and D'Astous propose entropy calculation over power spectrum region.

More recently multi-resolution or multi-channel analysis like Gabor filters and wavelet transform have been presented. Wavelet transform has the advantage of a precise and simple framework for analyzing the signal.

III. GABOR FILTER BASED TEXTURE EXTRACTION

Gabor filter is the Multiresolution technique used for minimizing the joint two-dimensional non-uniform distribution in space and frequency. A two dimensional Gabor function g(x, y) and its Fourier transformG(u, v) can be written as,

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right) exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x{}^2} + \frac{y^2}{\sigma_y{}^2}\right) + 2\pi jWx\right]$$

$$G(u,v) = exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u{}^2} + \frac{u^2}{\sigma_v{}^2}\right]\right\}$$

Where $\sigma_u = {}^{1}/_{2\pi\sigma_x}$ and $\sigma_v = {}^{1}/_{2\pi\sigma_y}$. Gabor filter is basically used for edge detection in the image and is a linear type of filter. Gabor filter mimic the human visual system and represents frequency and orientations. Gabor filters have direct mapping with Gabor wavelets.

IV. DISCRETE WAVELET TRANSFORM BASED FEATURE EXTRACTION

The discrete wavelet transform is the decomposition of an image into its subbands which are divided into low and high frequency components. LL component is the low pass component and contains the approximation of the image, other components LH1, HL1 and HH1 represents detail coefficient. The LL1 component can be further decomposed to have higher levels of decompositions. The advantages like Multiresolution analysis make it a good candidate for texture feature extraction. The transformation coefficients like vertical, horizontal, Detail and diagonal coefficient form a texture of the image which is used for different analysis of the image.

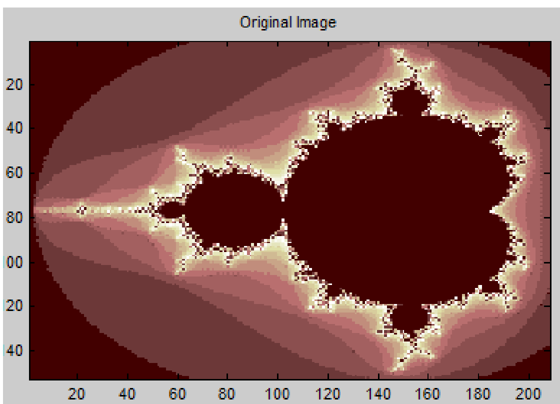

Fig: Orignal Image

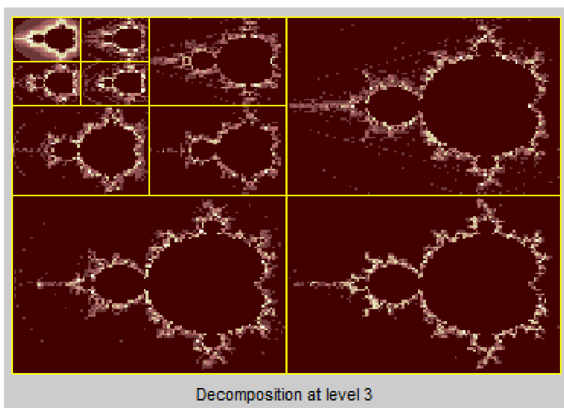

Fig: Wavelet transform at level 3

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Microtexture and macrotexture are the features that have non-uniform gray level variations and are characterized by the features in approximation and detail images. The subband images and its combinations form the feature of the image. Below figure shows the image and its 3 level wavelet transform.

V. TEXTURE CALCULATION

In the texture parameter calculation, mean and standard deviation are calculated for different levels of decomposition using wavelet transform, the equations for mean and standard deviation are below,

$$Mean(m) = \frac{1}{N^2}\sum_{i,j=1}^{N} p(i,j)$$

$$Standard\ Deviation(SD) = \sqrt{\frac{1}{N^2}\sum_{i,j=1}^{N}[p(i,j) - m]^2}$$

$$Digonal\ Moment, D(v) = \frac{\sum_{j=1}^{p} iS(i,i,v)}{\sum_{j-1}^{p} S\,(i,i,v)}$$

where p(i,j) is the transformed value in (i,j) for any sub-band of size N *N. with this procedure, the texture feature up to desired level is computed and yield a better result. In order to better visualization of the image co-occurrence gray level can be computed and other parameters like entropy and other stuff can be calculated.

VI. EXPERIMENTAL RESULTS

The below figures shows the histograms obtained by wavelet transform for the image shown above. The level one wavelet transform was applied to the image and four subbands was obtained for each histograms are given below,

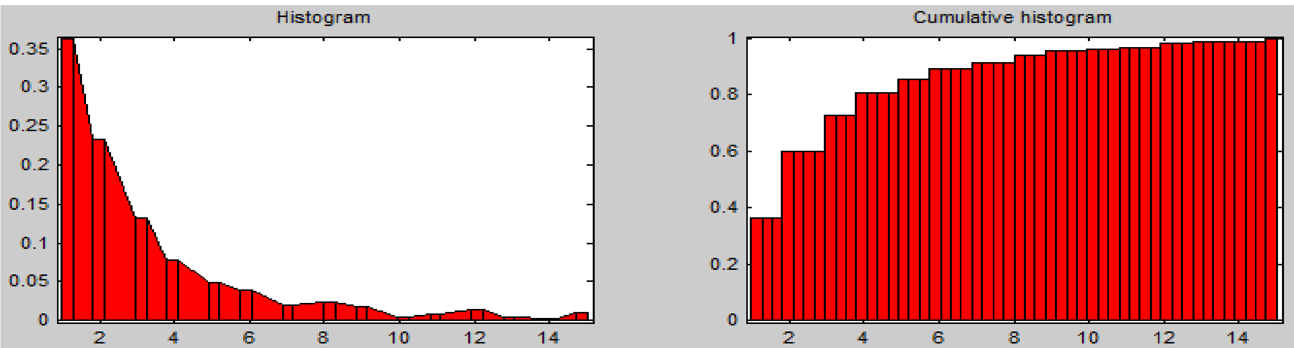

Fig: Histogram(Original Image)

After applying wavelet transform four subbands of the image is obtained. Namely LL, LH, HL and HH. The histograms of all the subbands contain useful information for extracting texture features. The histograms of all the subbands are shown below, The approximation details which is comparable to the original image is having histogram shown in blue, and other details like horizontal, vertical and diagonal details contain less information about the main image, the histograms of these components are shown in green below.

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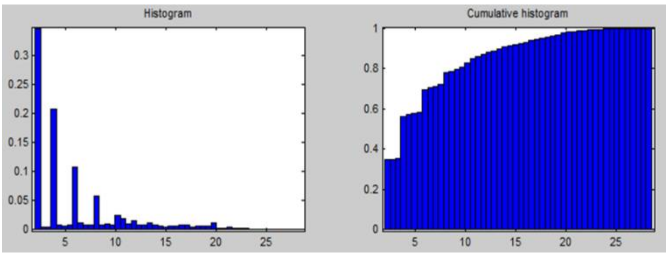

Fig: Approximation Details

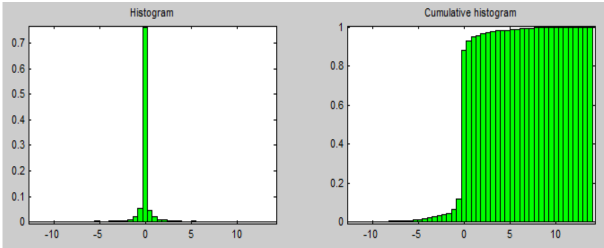

Fig: Horizontal Details

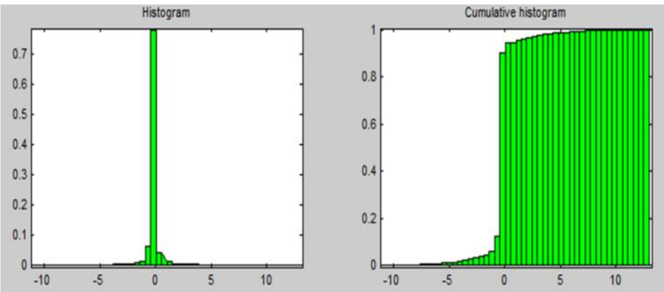

Fig: Vertical Details

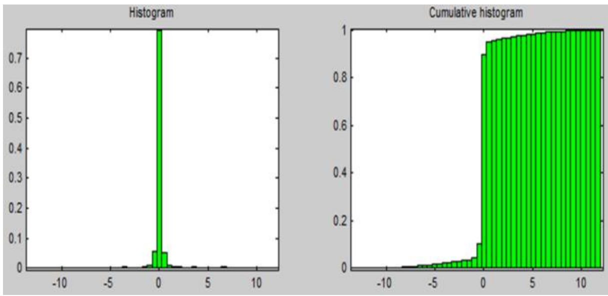

Fig: Digonal Details

VII. CONCLUSION

Different approaches for texture feature extraction have been presented. One method can be adopted depending upon the application. Transform based method showed better extraction parameters and values. The wavelet based method shows better results in terms of good and qualitative features and it time and frequency localization features of images. Texture features at any level can be determined and the parameters such as mean, standard deviation and moment can be calculated for the analysis and finding complex image pattern in the image. The coefficients obtained with the wavelet transform could be one of the parameters in finding the features. Histograms obtained after wavelet transform is another way to find the features in the image.

REFERENCES

1. R. M. Haralick, “Statistical and structural approaches to texture” , Proc. IEEE 67,pp 786-804, 1979.
2. K. L. laws, “Textued image Segmentation”, Technical Report USCIPI Report 940, Dept of Elec. Eng., Image Processing Institute, Univ. of Southern California, Los Angeles, January 1980.
3. R. W. Conners, M. M. Trivedi, and C. A. harlow, “Segmentation of high-resolution urban scene using texture operators”, Computer Vision Graphics Image Process. 25, pp273-310, 1984.
4. A.C. Bovic, M. Clark, and W.S. Geisler, “Multichannel Texture Analysis Using Localized Spatial Filters”, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 12, no. 1, pp. 55-73, Jan. 1990.
5. R. M. haralick, K. Shanmugam and I. Dinstein, “Textural features for image classification”, IEEE Trans. Systems Man Cybernet. 3(1), , 610-621, 1973.
6. I. Dinstein, A. C. Fong, L. M. Ni, and K.Y. Wong, “Fast discrimination between homogenous and textured regions”, In Proceedings, 7th International Conference on Pattern Recognition, pp. 361-363, 1984.
7. R. wang, A.R. Hanson, and E.M. Riseman, “Texture analysis based on local standard deviation of intensity”, IEEE Computer Society Conference on Computer Vision and Pattern Recognition,pp. 482-488,1986.
8. G.H. Granlund, “Description of texture sing the general operator approach”, in Proceedings, 5th International conference on Pattern Recognition, Miami Beach, Florida, December 1-4,pp. 776-779, 1980.
9. D. Wermser and N. Lissel, “Comparison of algorithms for unsupervised segmentation of images by the use of texture information”, in Proceedings of the 2nd European Signal Processing Conference, Erlangen, Wet Germany,pp. 287-290, 1983.
10. L.W. Abele, “Feature selection by spaveinvariany comparison with applications to the segmentation of textured pictures” , in Proceedings of the 5th International Conference on Pattern Recognition, Miami Beach, pp. 535-539, 1980.

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11. P. C. Chen and T. Pavlidis, "Segmentation b texture using a co-occurrence matrix and a split-and-merge algorithm", Computer Graphics Image Process,pp 172-182, 1979.
12. H. Knutsson and G.H. Granlund, "Texture analysis using two dimensional quadrature filters", IEEE workshop CAPAIDM, Pasadena, CA, pp.206-213, 1983
13. P. A. Dondes and A. Rosefeld, "Pixel classification based on gray level and local busyness" , IEEE Trans, Pattern Anal. Mach. Intell, 4(1), pp.79-84, 1982
14. H.Y. Lee, "Extraction of textured regions in aerial imagery", in Image Understanding, Proceedings, Workshops, Arlington, VA, June 23, 1983(L.S. Baumann, Ed.), pp. 298-303, 1983.
15. G.Y. Xu and K.S. Fu, "Natural scene segmentation based on multiple threshold and texture measurement", in Proceedings, 7th International Conference on Pattern Recognition", pp. 1111-1113, 1984.
16. W.Y. Ma and B.S. Manjunath, "A Comparison of Wavelet Features for Texture Annotation" Proc. IEEE Int'l Conf. Image Processing '95, vol. 11, pp. 256-259, Oct. 1995.
17. M. E. Jernigan and F.D'Astous, Entropy-based texture analysis in the spatial frequency domain, IEEE Trans, pattern Anal. Mach. Intell, 6(2), pp237-243, 1984.
18. Robert m. Haralick, k. Shanmugam, and its'hakdinstein, "Textural Features for Image Classification", IEEE transactions on systems, man, and cybernetics, vol smc-3, no. 6,, pp. 159-166, 1973
19. D. Harwood, T. Ojala, M. Pietiktiinen, S. Kelman and L. S. Davis, Texture classification by center-symmetric auto-correlation, using Kullback discrimination of distributions, Pattern Recognition Lett. 16(1), pp1-10, 1995.
20. Vadivel, R and V. MuraliBhaskaran,'Energy Efficient with Secured Reliable Routing Protocol (EESRRP) for Mobile Ad-Hoc Networks', Procedia Technology 4,pp. 703- 707, 2012.

BIOGRAPHY

Binay Chandra is pursuing M.Tech degree in VLSI and Embedded system design from Pune University. His M.Tech thesis is on FPGA implementation of BioMedical image processing and texture feature extraction using wavelet transform. He gained his Bachelor's degree from BharatiVidyapeethUniversity in 2011. His area of interests are Image processing, Internet of things and Neural Networks.