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SKIN TEXTURE ANALYSIS FOR MEDICAL DIAGNOSIS - A REVIEW

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ABSTRACT

As the technicality in the day to day life is increasing, the world is getting highly dependent on different devices for almost each and every work. Every individual is dependent on these devices for accurate and efficient results. Also, the manual work has been reduced to a great extent. Skin texture analysis is one of the major issues in the field of medical diagnosis. Various types of skin diseases are affecting human life. To treat in an efficient and significant manner and to provide the best ailment, the disease has to be diagnosed properly. Hence, the texture of skin is analysed based on various features and characteristics so that the discrepancies can be avoided during the treatment. Therefore, the purpose behind this review paper is to create a base for the research and introduction of the algorithm that is to be used for the same i. e. GLCM and Wavelet Decomposition method.

Keywords: Diagnosis,GLCM, Haar Wavelet, Markov Random Field, Skin Diseases.

I INTRODUCTION

Texture and colour of human skin has proven to be the most important aspect of several imaging systems. Human texture reproduction has been very beneficial in medical diagnosis, cosmetic analysis etc. [1].The basis on which the human is able to discriminate between surfaces and objects is texture analysis. The skin texture has a close relation with the individual's diet, hormones, hydration and any allergic symptoms.[2] Various properties correlate with the skin texture e.g. skin dryness, fungus, allergic symptoms etc.

Significant amount of work has been performed on analysis of the skin texture till date. Previously the image is analysed for extracting haemoglobin and melanin components by independent component analysis. The image has been synthesized for the comparison. [3]

The skin colour image is also decomposed by YuantingGu and Enhua Wu to the four texturecomponents by multi-resolution analysis using wavelettransform for synthesizing the image and separating it from the original image. [4]

Texture contents are also decomposed for separating the image of skin into the basic shape and the feature vector based on which the texton (pixel) change is observed to determine the pattern and structure. This process is done under image synthesis.

The filtering method is also introduced which is applied todermoscopic skin image in a non-linear manner and allowsselective image filtering. This feature is highly desirable dueto the fact that in most cases of computer aided diagnostic,input images need to be pre-processed (e.g.for brightnessnormalization, histogram equalization, contrastenhancement, color normalization) and this can results inunwanted artifacts or simply may require human verification. [5]

Anil Kumar Mittra in his paper proposed anautomated system for recognizing disease conditions ofhuman skin in context to health informatics. The diseaseconditions are recognized by analysing skin texture imagesusing a set of normalized symmetrical Grey Level Co-occurrenceMatrices (GLCM).[6]

Texture of anything is the way it appears and to analyse or study the texture of skin for example various components and features needs to be studied and worked upon so that the proper and accurate analysis can be done. This analysis will result into the error free diagnosis of the texture and skin diseases in particular. Few of the components being contrast, energy, entropy etc. Therefore, this paper will discuss all the essential components and the ways that can be used and implemented to analyse those components. Primarily the focus will be on the GLCM (Gray Level Co-occurrence Matrix) that works on the gray scale image and the wavelet decomposition method which is one of the appropriate method for extracting the features of an image .

II TEXTURE

As the definition for image texture is not exact but vary, itgives us information about the spatial arrangement of colour or intensities in an image or selected region of an image. It is what is identified by humans and is supposed to be a valuable source of visual information – about the nature and 3Dshape of objects. Usually, textures are complex visual patterns comprising entities, or sub-patterns, having characteristic brightness, colour, slope, size, etc. The local sub-pattern properties lead to the anticipated lightness, uniformity, density, roughness, regularity, linearity, frequency, phase, directionality, coarseness, randomness, fineness, smoothness, granulation, etc., of the texture. Issues involved in texture analysis are as follows:

- Feature extraction: to compute a characteristic of a digital image able to numerically describe its texture properties;
- Texture discrimination: to partition a textured image into regions, each corresponding to a perceptually homogeneous texture (leads to image segmentation);
- Texture classification: to determine to which of a finite number of physically defined classes (such as normal and abnormal tissue) a homogeneous texture region belongs;
- Shape from texture: to reconstruct 3D surface geometry from texture information.

Feature extraction is the first stage of image texture analysis. Results obtained from this stage are used for texture discrimination, texture classification or object shape determination. This review is confined mainly to feature extraction and texture discrimination techniques. Most common texture models will be shortly discussed as well. [7]

2.1 Texture analysis

Texture analysis approaches are broadly categorised into 4 methods. They are

_ structural
_ statistical
_ model-based and
_ transform.

Structural approach depicts texture by well-definedprimitives (microtexture) and a hierarchy of spatial arrangements (macrotexture) of those primitives. Defining the primitives and theplacement rules, describes the texture very well. The choice of a primitive (from a set of primitives) and the probability ofthe chosen primitive to be placed at a particular location can be a function of location or the primitives near the location. Good symbolic description of the image is the pros of structural approach ;which is however useful for synthesis rather than analysis. A powerful tool for structural texture analysis is provided bymathematical morphology. It may prove to be useful for boneimage analysis, e.g. for the detection of changes in bone microstructure.[7]

Whereas**Statisticalapproach** do not attempt to understandnotably the ordered structure of the texture. Rather, they represent the textureindirectly by the non-deterministic properties that control the distributions andrelationships between the gray levels of an image. Methods based on second-orderstatistics (i.e. statistics given by pairs of pixels) have been shown to achieve higherdiscrimination rates than the power spectrum (transform-based) and structural methods. Accordingly, the textures in gray-level images arediscriminated spontaneously only if they differ in second order moments. Equal secondordermoments, but different third-order moments require calculative effort.

There are two classes of image segmentation namely, supervised and unsupervised learning process. In supervised learning process the output is attached along with the input as there is a prior knowledge of the pixel in the image also the training pattern is known beforehand. In contrast to this in unsupervised learning process there is no prior knowledge about the pixel and labelling of the class. Knowing the pattern in advance helps in minimizing the sum of cost of functions of all the patterns.[8]

Statistics up to the second order may be most important for automatic processing. For texture analysis the most popular second-order statistical features are derived from the so-called co-occurrence matrix. They were demonstrated to feature a potential for effective texture discrimination in biomedical-images. When applied to texture classification the approach based on multidimensional co-occurrence matrices was recently shown to outperform waveletpackets (a transform-based technique).

Model based texture analysis 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. In practice, the primary problem is the computational complexity arising in the estimation of stochastic model parameters. The fractal model is useful for modelling some natural textures. For texture analysis and discrimination it can be used as well but, it is not suitable for describing local image structures.

Transform methods of texture analysis, such as Fourier, Gabor and wavelet transforms 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). Due to its lack of spatial localisation methods based on the Fourier transform perform poorly in practice. Gabor filters provide means for better spatial localisation; however in practice, their usefulness is limited because there is usually no single filter resolution at which one can localise a spatial structure in natural textures. The wavelet transforms have various advantages compared with the Gabor transform:

_ textures can be represented at the most suitable scale by varying the spatial resolution,

_ one can choose wavelets best suited for texture analysis in a specific application as there is wide range of choices for the wavelet function. They make the wavelet transform attractive for texture segmentation. The disadvantage with wavelet transform is that it is not translation-invariant.

2.2 Models of texture

Models used for image segmentation are AR model, Gaussian-Markov RMF, Gibbs RMF.These models are used for feature extraction.

2.2.1 AR models

The autoregressive (AR) model assumes a local interaction between image pixels in thatpixel intensity is a weighted sum of neighbouring pixel intensities. AR model works for both the rough and smooth images.

Causal AR models are simple and efficient as compared to the other non-causal spatial interaction models. Causal AR model parameters were usedfor unsupervised texture segmentation.

AR model is used for image segmentation in identifying the parameters(modal)for a given image region and then using those parameter values for texturediscrimination.

Repeatedly identified parameters of this model were used in for segmentation using an Artificial Neural Network.

2.2.2 Markov Random Fields

A Markov random field (MRF) is a possible process where all interactions are local;the possibility that a cell is in a given state is completely determined by probabilities forstates of neighbouring cells. Direct interaction occurs only between immediate neighbours. The result of propagation is the global effects.The lower the energy of a particular image (that was generated by aparticular MRF), the more likely it is to occur.There is an advantage in hidden Markov models (HMM) over other texturediscrimination methods is that an HMM attempts to discern an underlying fundamental structure of an image that may not be directly observable. [7] The other traditional method segments statistical texture image by maximising the aposteriori probability based on the Markov random field (MRF) and Gaussian randomfield models. Gibbs random field is used by the MAP (Maximize the posteriori) estimator because MRF does not give the accurate conditional probability density function (pdf). However, the Gibbs parameters are not known a priori,thus they should be estimated first for texture segmentation.

An efficient GMRF parameter estimation method, based on the histogramming technique is elaborated in (Gurelli 1994). It does not require maximisation of a loglikelihoodfunction; instead, it involves simple histogramming, a look-up table operationand a computation of a pseudo-inverse of a matrix with reasonable dimensions. [3]

Merging process is the last stage of segmentation process where the conditional likelihood of image is maximised. The problem of selectingneighbours during the design of colour RMF is still to be investigated. The analysis proved that samples has sufficientinformation to differentiate between different textures and that the MRF model does not have a good performance as it does not provide accurate model of the texture for various images.

Multi-resolution method has proven to be more accurate in comparison to the single resolution as it uses GMRF for texture segmentation (Krishnamachari 1997).Fine resolution is obtained from the result of the segmented coarse resolution.

III TEXTURE ANALYSIS TECHNIQUES

Texture features can be extracted from methods such as GLCM, Haar Wavelet Decomposition and Wavelet GLCM fusion etc.

3.1Gray Level Co-Occurrence Matrix (GLCM)

The texture of an image can be found out by constructing 2D array of pixels of the image. This 2D array is known asGray Level Co-occurrence Matrix (GLCM). The GLCM(Gray-level co-occurrence matrix) is a statistical technique of imageanalysis that calculates image properties upto second order. Both the structural and statistical properties of the image can be defined using GLCM. This matrix is calculated by considering the two neighbouring pixels and the probability of their co-occurrence in the image at a given offset. The first pixel is the reference pixel and the other one is the neighbouring. The matrix is calculated along the four directions i.e. horizontal, vertical, right diagonal, left diagonal. The angles associated are 0 deg, 45deg, 90deg, 135deg. These are then normalised to get the desired output.The GLCM is totally dependent on directions. GLCM elements are G (i, j, d, Ө) where I is the reference pixel, j is neighbouring pixel, dis the sample distance between pixels and Ө is the angle along which the matrix has been calculated.

GLCM FEATURES

S.NO	FEATURE	FORMULA
1	MeanX	$\mu_i = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} i\, p(i,j)$
2	MeanY	$\mu_j = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} j\, p(i,j)$
3	Standard DeviationX	$\sigma_i = \sqrt{\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} p(i,j)(i-\mu_i)}$
4	Standard DeviationY	$\sigma_j = \sqrt{\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} p(i,j)(j-\mu_j)}$
5	Contrast	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} p(i,j)(i-j)^2$
6	Dissimilarity	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} p(i,j)\lvert i-j\rvert$
7	Homogeneity	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} \frac{p(i,j)}{1+(i-j)^2}$
8	Entropy	$-\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} p(i,j)\log p(i,j)$
9	Energy	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} p(i,j)^2$
10	Correlation	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} \frac{\lvert ijp(i,j)-\mu_i\mu_j\rvert}{\sigma_i\sigma_j}$

Fig:1 Features From GLCM

GLCM is used to calculate various features such as homogeneity (uniformity of the image), entropy (randomness), contrast (vividness of the pattern of texture), energy (pixel pair repetition) etc. Though GLCM has various problems, still it is used to calculate various features that are quiet relevant. Features extracted using GLCM are shown in following Fig: [9]

3.2 Haar Wavelet

The space domain of an image is transformed to a local frequency domain using Haar wavelets. Haar wavelet consists of filters namely low pass and high pass filters series of which is known as filter banks. These filter banks are used by the discrete wavelet transform for wavelet analysis and division of the image into different frequency bands mainly 4 sub bands at each level. The bands are LL, HL, LH, HH from which the approx. image is given by LL and the other informs about directions. The information hence obtained is orientation sensitive also decomposition does not lose anything. This technique also has few disadvantages e. g. producing large number of signatures and not being continuous.This method consists of following features shown in the Fig below: [9]

$$\text{Mean}=\frac{1}{(N*M)}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}P[i][j]$$

Standard deviation

$$=\sqrt{\left(\frac{1}{(N*M)}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}\left(P[i][j]-Mean\right)^{2}\right)}$$

Fig:2Features From HAAR Wavelet

Also,the bands involved in the wavelets are shown in the following Fig:

LL	HL
LH	HH

Fig:3 Wavelet Bands

3.3 Blending GLCM and Haar

When the two techniques i.e. GLCM and Haarwavelet is combined together for extracting the texture features of an image, the result is efficient and the performance is better than using them separately as the bands of the Haar wavelet and the orientation elements of GLCM are completely related to each other. Because GLCM requires an additional array to store the averaging and differencing results of the bands hence, Haar wavelet can be used to precisely put it on the input image. As a result the calculation is reduced from the original GLCM. And hence the result is more accurate and robust to variations.

3.4 Skin and the Texture

Since, the texture is the basis on which one can easily differentiate between objects. Every object has different type of textures and similarly the types of textures of skin varies. Therefore, to analyse the skin texture and extract the features from it the above methods can be used. These methods can be implemented as system which can then be used by various dermatologists to diagnose skin diseases accurately and efficiently. This system will improve the detection of diseases and its treatment. It will also decrease the manual work which will automatically decrease the errors which can be caused due to less skilled people such as in rural areas. In addition to it the area or the region of interest i.e. the affected area can be easily determined etc.

IV CONCLUSION

The paper describes various techniques and models that has been used till now for the feature extraction of the image. These methods have shown great results in various fields but still needs some improvements. When the extraction is to be done in the field of medical it has to be very accurate so that the proper treatment can be given to the concerned patient. Therefore to make the observations as accurate as it can be the methods and techniques will be worked upon and implemented. Although the technique of GLCM has proven to be very near to accurate , it has few drawbacks which can be removed usingHaar wavelet technique along with it.

SIZE OF FEATURE VECTOR

S.NO	TECHNIQUE	SIZE OF FEATURE VECTOR
1	GLCM Features	10
2	Haar Wavelet	2*(Depth*3+1)
3	WaveletGLCM Fusion Technique 1	20
4	WaveletGLCM Fusion Technique 2	60(10 Features For Each Of The 6 Bands)

Fig:4 Number Of Features According To The Techniques

TIME TAKEN by EACH TECHNIQUE

S.No.	Technique	Time Taken (HH:MM:SS:MS)	
		Figure 1	Figure 2
1	GLCM	00:00:03:385	00:00:02:556
2	Wavelet	00:00:00:905	00:00:00:717
3	Fusion 1	00:00:00:983	00:00:01:014
4	Fusion 2	00:21:27:826	00:20:00:610

Fig:5 Time Taken By Each Technique

Form the results shown in Fig. 4 [9] and Fig. 5 [9] it is evident that when GLCM and Haar Wavelet alone is used the features extracted are lesser in number. On the other hand when they are implemented together the results are quiet appreciable [9]. But there are two techniques that are being used and the selection of the technique depends upon the necessity of the user i.e. if time is given importance then technique 1 has to be preferred as it given the output in lesser amount of time but the number of features extracted are less whereas, if the output is given importance, technique 2 has to be preferred because it gives significant output but takes more time as compared to the technique1. [9]

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