Texture Analysis and Classification Using Wavelet Extension and Gray Level Co-occurrence Matrix for Defect Detection in Small Dimension Images

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Abstract: Texture analysis is an important role for automatic visual insfection. This paper presents an application of wavelet extension and Gray level co-occurrence matrix (GLCM) for detection of defect encountered in textured images. Texture characteristic in low quality images is not to easy task to perform caused by noise, low frequency and small dimension. In order to solve this problem, we have developed a procedure called wavelet image extension. Wavelet extension procedure is used to determine the frequency bands carrying the most information about the texture by decomposing images into multiple frequency bands and to form an image approximation with higher resolution. Thus, wavelet extension procedure offers the ability to robust feature extraction in images. Then the features are extracted from the co-occurrence matrices computed from the sub-bands which performed by partitioning the texture image into sub-window. In the detection part, Mahalanobis distance classifier is used to decide whether the test image is defective or non defective.

Keywords: *Texture defect detection, Wavelet extension, Co-occurrence matrices, feature extraction.*

1. INTRODUCTION

Textures provide important characteristics for surface and object identification from aerial or satellite photograph, biomedical images, and many other types of images. Their analysis is fundamental to many applications such as industrial monitoring of product quality, remote sensing of earth resources, and medical diagnosis with computer tomography. Much research work has been done on texture analysis, such as classification, compression, retrieval and segmentation for last three decades. Despite the effort, texture analysis is still considered an interesting but difficult problem in image processing [6],[11],[12].

A number of approached to solve the texture analysis and classification problem has been developed over the years. Early research work was based on the first-order and second order statistics of texture, Gaussian Markov random field , fractal models and local linear transform [1],[2],[3],[4]. Recently, some modern methods have been developed, such as multichannel method, multiresolution analysis, Gabor filter and the wavelet transform [7],[9] note that many of these approaches have provided good results in different fields of application but a large number of them have shown very low classification rate or could not be implemented at all when texture samples are of small dimensions.

The objective of this thesis is to observe the algorithms for texture analysis and classification, which can be detected by texture image as a textural normal pattern different from the abnormal pattern. A new algorithm is proposed for improving quality of texture result. The main idea of the new algorithm lies in the successive decomposition of the input image with wavelet basis functions, and the synthesis of new image with higher resolution. Aleksandra Mojsilović *et. al* [9] showed that, from the texture characterization perspective, the proposed decomposition scheme performs more efficient energy distribution of an image, and the first-order, second order, and higher-order statistics calculated on the expanded images can be used as reliable texture descriptors for classification purpose.

This paper is organized as follow. Section 2 introduces background theory of wavelets and co-occurrence matrices. Section 3 describes step by step the methodology of the research. Experimental results are presented in section 4, and finally, in section 5, includes the concluding remarks.

2. MATHEMATICAL MODELLING

2.1. Wavelet Transform

The wavelet transform is define as a decomposition of signal *f(t)* with a family of real orthonormal bases $\psi_{m,n}(t)$ generated from a kernel function $\psi(t)$ by dilations and translations [5],[8],[13]:

$$\psi_{m,n}(t) = 2^{-m/2}\,\psi(2^{-m}t - n) \tag{1}$$

where j and k are integers. The mother wavelet $\psi(t)$ has to satisfy

$$\int \psi(t)\,dt = 0 \tag{2}$$

Since $\psi_{m,n}(t)$ forms an orthonormal set, the wavelet coefficients of the signal *f(t)* can be calculated by the inner product

$$c_{m,n} = \int f(t).\psi_{m,n}(t)\,dt \tag{3}$$

For the wavelet expansion, signal *f(t)* can be reconstruction via

$$f(t) = \sum_{m,n} c_{m,n}.\psi_{m,n}(t) \tag{4}$$

The multiresolution formulation needs two closely related basic functions. In addition to the mother wavelet $\psi(t)$, we will need another basic function, called the scaling function $\phi(t)$. $\phi(t)$ can be expressed in term of weighted sum of shifted $\phi(2t)$ as [3]:

$$\phi(t) = \sqrt{2}\sum_k h(k)\,\phi(2t-k) \tag{5}$$

where *h(k)'s* are the scaling function (lowpass) coefficients, and the $\sqrt{2}$ maintains the norm of the scaling function with the scale of two. The scaling coefficients *h(k)* must satisfy

$$\sum_k h(k) = \sqrt{2} \tag{6}$$

and

$$\sum_k h(k)\,.\,h(k-2n) = \begin{cases} 1 & \text{if } k=0 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

The dilation equation above (Eq.1) is fundamental to the theory of scaling function. The mother wavelet $\psi(t)$ is related to the scaling function via

$$\psi(t) = \sqrt{2}\sum_n g(k)\,\phi(2t-k) \tag{8}$$

where *g(k)'s* are the wavelet (highpass) coefficients. They are required by orthogonallity to be related to the scaling coefficients by

$$g(k) = (-1)^k\ h(1-k) \tag{9}$$

The mother wavelet $\psi(t)$ is good at representing the detail and high-frequency parts of a signal. The scaling function $\phi(t)$ is good at representing the smooth and low-frequency parts of the signal.

In most practical applications, one never explicitly calculates the scaling function $\phi(t)$ and wavelet $\psi(t)$, but perform the transform using the scaling coefficient *h(k)* and the wavelet coefficients *g(k)*. In forward wavelet analysis, a *j*-level discrete decomposition can be written as

$$f(t) = \sum_n c_{o,k}\ \phi_{o,k}(t)$$

$$= \sum_k c_{j+1,k}\ \phi_{j+1,k}(t) + \sum_{j=0}^{J}\sum_k d_{j+1,k}\ \psi_{j+1,k}(t) \tag{10}$$

where coefficients $c_{o,k}$ are given, and coefficients $c_{j+1,n}$ and $d_{j+1,n}$ at resolution *j+1* are related to the coefficients $c_{j,n}$ at level *j* by the following recursive equation:

$$c_{j+1,n} = \sum_k c_{j,k}\ h(k-2n)$$

and (11)

$$d_{j+1,n} = \sum_k c_{j,k}\ g(k-2n)$$

where $0 \le j \le J$. Thus, (11) provides a recursive algorithm for wavelet decomposition through *h(k)* and *g(k)*, and the final outputs include a set of J-level wavelet coefficients $d_{j,n}$, $1 \le j \le J$, and $c_{j,n}$

$$c_{j,k} = \sum_n c_{j+1,n}\ h(k-2n) + \sum_n d_{j+1,n}\ g(k-2n) \tag{12}$$

It is convenient to view the decomposition (11) as passing a signal $c_{j,k}$ through a pair of filters H and G with impulserespon $\hat{h}(n)$ and $\hat{g}(n)$ and downsampling the filtered signals by two (dropping every other sample), where $\hat{h}(n)$ and $\hat{g}(n)$ are define as

$$\hat{h}(n)=h(-n) \text{ and } \hat{g}(n)= g(-n) \tag{13}$$

The pairs filter H and G correspound to the halfband lowpass and highpass filter, respectively, and are called the quadrature mirror filters in the signal processing literature. The reconstruction procedure is implemented by upsampling the subsignal c_{j+1} and d_{j+1} (inserting a zero between neighboring samples) and filtering with *h(n)* and *g(n)*, respectively, and adding these two filtered signals together. Usually the signal decomposition scheme is performed recursively to the output of the lowpass filter $\hat{h}$. It leads to the conventional wavelet transform or the so-called pyramid-structured wavelet decomposition [2].

The 1-D multiresolution wavelet decomposition can be easily extended to two dimensions by introducing separable 2-D scaling and wavelet functions as the tensor product of their one-dimensional complements.

$$\phi_{LL}(x,y) = \phi(x)\phi(y)$$
$$\psi_{LH}(x,y) = \phi(x)\psi(y)$$
$$\psi_{HL}(x,y) = \psi(x)\phi(y)$$
$$\psi_{HH}(x,y) = \psi(x)\psi(y)$$

The corresponding filter coefficient are

$$f_{LL}(x,y) = h(x)\,h(y)$$
$$f_{LH}(x,y) = h(x)\,g(y)$$
$$f_{HL}(x,y) = g(x)\,h(y)$$
$$f_{HH}(x,y) = g(x)\,g(y)$$

where the first and second subscripts denote, respectively, the lowpass and highpass filtering along the row and column direction of the image.

Figure 1 shows how to implement the wavelet decomposition of an image. After the decomposition, four subbands, LL, LH, HL and HH subbands, which represent the average, horizontal, vertical, and diagonal information respectively.

In order, we use a procedure called wavelet image extension. The application of the procedure is illustrated by the block diagram in Figure 3a. These four images are used as the input into the extension (interpolation) procedure, which is illustrated by the block diagram in Figure 3b.

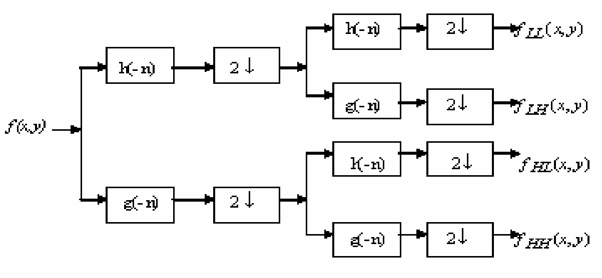


Fig.1. One stage in multiresolution image decomposition

2.2. Co-occurrence Matrices

The co-occurrence matrix is defined by a distance and an angle, and its mathematical definition is

$$P_d[i,j] = \left|\{[r,c] : I[r,c] = i \text{ and } I[r+dr, c+dc] = j\}\right|$$

where d be a displacement vector (dr, dc) specifying the displacement between the pixel having values i and the pixel having value j, dr is a displacement in rows (downward) and dc is a displacement in columns (to the right) and I denote an image of size NxN with G gray values [10].

Texture classification can be based on criteria (feature) derive from the occurrence matrices.

1). Entropy

$$ENT = -\sum_i \sum_j p(i,j) \log p(i,j) \tag{14}$$

2). Contrast

$$CON = \sum_i \sum_j (i-j)^2 p(i,j) \tag{15}$$

3). Angular Second Moment

$$ASM = \sum_i \sum_j \{p(i,j)\}^2 \tag{16}$$

4). Inverse Difference Moment

$$IDM = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j) \tag{17}$$

In Equation (14) – (17), *p(i,j)* refers to the normalized entry of the co-occurrence matrices. That is

$$p(i,j) = \frac{p_d(i,j)}{R} \tag{18}$$

where R is the total number of pixel pairs *(i,j)*. For a displacement vector *d = (dr,dc)* and image of size *NxM R* is given by *(N-dr)(M-dc)*.

3. TEXTURE DEFECT DETECTION

The proposed defect detection system consist of two stages [10]: (i) The feature extraction part which first utilizes the wavelet extension procedure to decompose textured image into subbands and (ii) The detection part (texture classification) which is a mahalanobis distance classifier being trained by defect free samples (see fig.4).

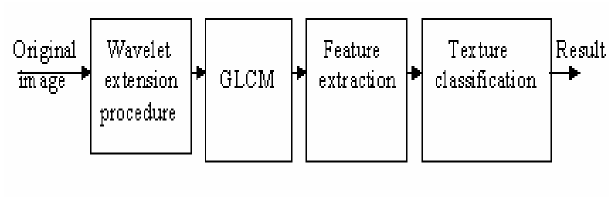


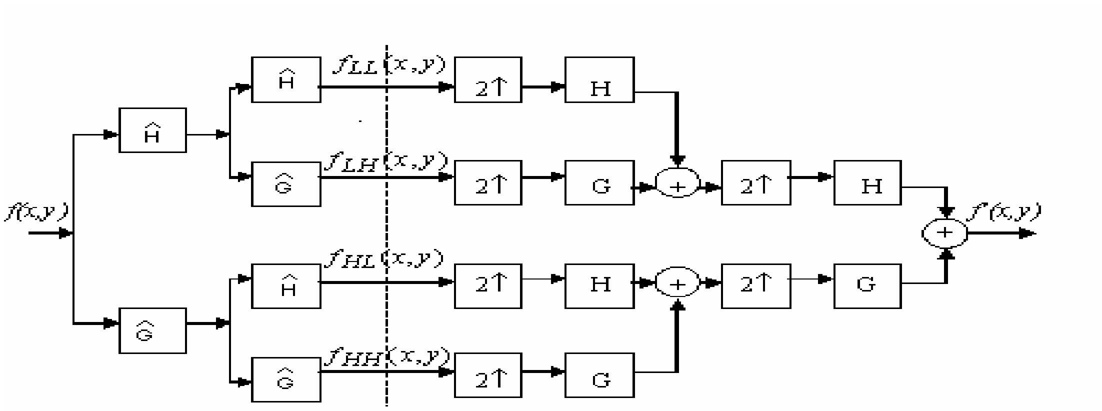
Fig.4 Block diagram of the system

3.1. Step in the feature extraction phase

1). Decompose a texture image at the original resolution k=0 into the four frequency channels, $f_{k(LL)}$, $f_{k(LH)}$, $f_{k(HL)}$, $f_{k(HH)}$ respectively.
2). Calculate the energy Eo for the original image, as well as the energy values $E_{0(LL)}$, $E_{0(LH)}$, $E_{0(HL)}$, and $E_{0(HH)}$.
3). Using the four images as input to the extension procedure, form a new image f_{k+1}, having two times higher resolution.
4). Decompose the obtained image into the corresponding frequency channels $f_{k+1(LL)}$, $f_{k+1(LH)}$, $f_{k+1(HL)}$, $f_{k+1(HH)}$, calculate the energies E_{k+1}, $E_{k+1(LL)}$, $E_{k+1(LH)}$, $E_{k+1(HL)}$, and $E_{k+1(HH)}$
5). Repeat step 3) and 4) The criterion to stop further extension could be the difference between the energy of image with resolution k and the image with resolution k+1. If constraint

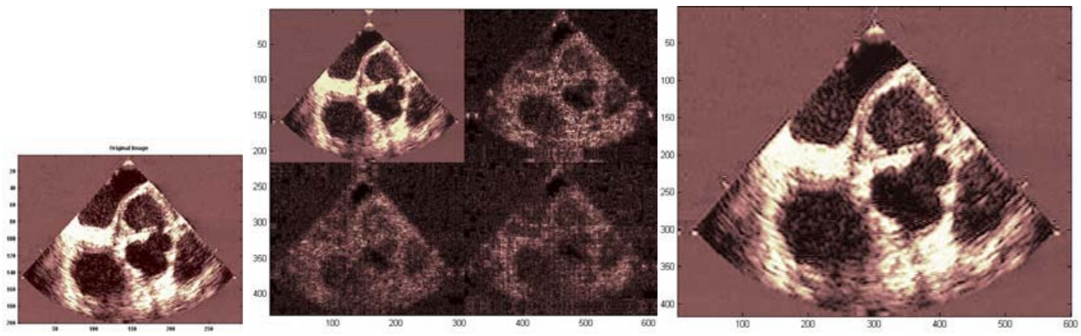
$$\partial c = \frac{|E_k - E_{k+1}|}{E_k} < \varepsilon$$

is not satisfied, the extension procedure should not be further performed because the energy values are significantly different.
6). Divide each sub-band images $f_{k+1(LL)}$, $f_{k+1(LH)}$, $f_{k+1(HL)}$, and $f_{k+1(HH)}$, into non-overlapping sub-images $S_{x,i}$ of size pxp, indices x and i denote sub-band and sub-image respectively.
7). Calculate the co-occurrence matrices P_θ for d = 1 and angles $\theta = (0, \pi/4, \pi/2, 3\pi/4)$ radians.
8). Calculate ENT, CON, ASM, IDM for each co-occurrence matrix.
9). Calculate the mean μ_x and standard deviation σ_x for each feature of four angles.
10). Construct the vector $f_{x,i}$ = [μ_{ENT} σ_{ENT} μ_{CON} σ_{CON} μ_{ASM} σ_{ASM} μ_{IDM} σ_{IDM}].
11). Repeat step 7) to 10) for all bands.
12). Feature vector for i-th sub-image S_i in the original image is constructed as:
$$S_i = [f_{LL,i} \; f_{LH,i} \; \ldots\ldots\ldots\ldots]^T$$
13). Repeat step 7) to 12) for all i.



(a) (b)

Fig. 3. Block diagrams illustrating the complete wavelet decomposition-extension procedure (a) the composition part and (b) the extension (synthesis) algorithm.



(a) (b) (c)

Fig. 4. The result of the complete decomposition-extension procedure for one representative ultrasound image of a human heart. (a) original image (b) after the decomposition (c) synthesized (reconstruction) image with two times higher resolution.

3.2. Detection Parts

1). Given k defect-free images, calculate the feature vector for each sub-image of the images using the feature extraction scheme given above. Consider these vectors as the true feature T_i

2). Compute the mean vector m and the covariance matrix C for the feature vector T_i

3). Given a test image calculate the feature vector S_i's using the feature extraction scheme given abobe.

4). Compute the mahalanobis distance d_i between each feature vector S_i and the mean vector m

$$d_i = (S_i - m)^T C^{-1} (S_i - m)$$

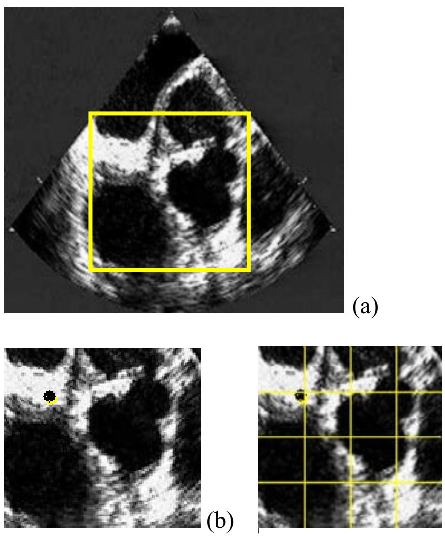
5). Classify a sub-image S_i for which d_i exceeds a threshold value α as defective, else idenfy it as nondefective i.e,

$$S_i = \begin{cases} defective \quad if \quad d_i > \alpha \\ nondefective \quad otherwise \end{cases}$$

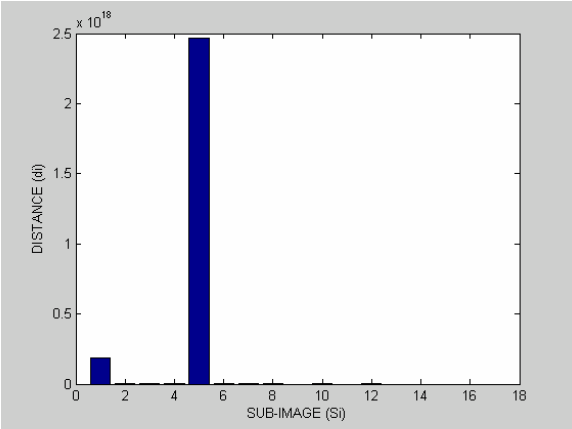
4. EXPERIMENTAL RESULTS

The experiments in this research are used texture image from echocardiography and some other texture from Brodat's with small dimension (≤ 128 x 128).

4.1. Ultrasound image of a human heart



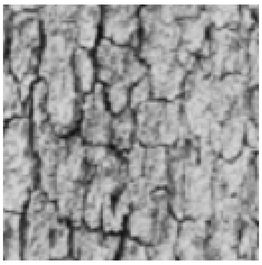
(a) (b) (c)



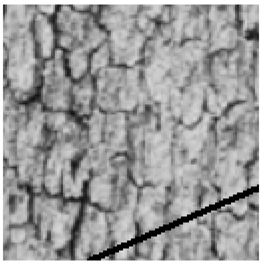
(d)

Fig. 5. Example of echocardiography image (a). Original image, (b). Sub-image, defective image, (c). Partitioned image into 32x32 sub-image, (d) Distance (di) values for the Sub-image (Si) of defective image of heart

4.2. Example of Brodat's texture



(a)



(b)

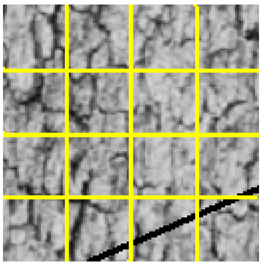


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Fig. 6. Example of bark texture (dimension 128x128), (a) non defective image (b) defective image (c) partitioned image inro 32x32 sub-image.

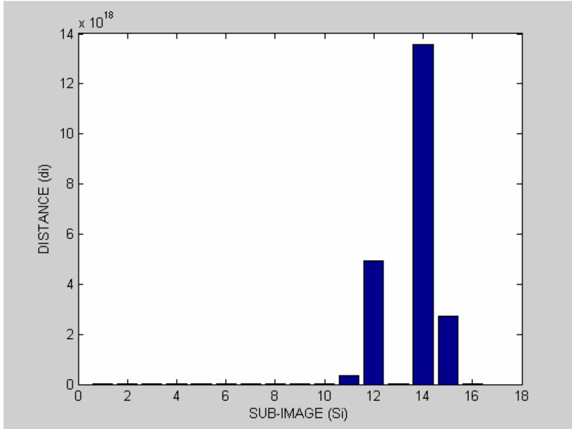

Fig. 7. Distance (di) values for the Subwindow (Si) of defective image of bark texture

5. CONCLUSIONS

The following conclusions can be drawn from our studies:

1). The new algorithm has advantages in classification of small and noisy input sample, and it represents a step a toward structural analysis of weak textures.

2). Texture analysis techniques will have useful application in medical images.

3). The clinical aspect of this research is probably the most important one. Accurate results obtained in classification for texture defect detection give rise to a new, advanced approach in various heart diseases.

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