Analysis and Classification of Myocardial Infarction Tissue from Echocardiography Images Based on Texture Analysis

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Abstract

Texture analysis is an important characteristic for automatic visual inspection for surface and object identification from medical images and other type of images. This paper presents an application of wavelet extension and Gray level co-occurrence matrix (GLCM) for diagnosis of myocardial infarction tissue from echocardiography images. Many of applications approach have provided good result in different fields of application, but could not implemented at all when texture samples are small dimensions caused by low quality of images. Wavelet extension procedure is used to determine the frequency bands carrying the most information about the texture by decomposition 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. The gray level co-occurrence matrices are computed for each sub-band. The feature vector of testing image and other feature vector as normal image classified by Mahalanobis distance to decide whether the test image is infarction or not.

Keywords*:* wavelet extension, feature extraction, myocardial infarction, co-occurrence matrices.

1. Introduction

Textures provide important role for automatic visual inspection. The ability to represent is the single most important step in the development of system for measuring the similarity of textures and segmenting images on the basis of differences in textures. Their analysis is fundamental to many applications such as industrial monitoring of product quality control, 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 [4], [6],[11],[12].

Acute myocardial infarction is caused by the obstruction of a coronary artery by a thrombus, leading to irreversible damage of the heart muscle (myocardium). Echocardiography is a diagnostic test that uses ultrasound waves to create an image of the heart muscle. It may show such abnormalities as poorly functioning heart valves or damage to the heart tissue after acute myocardial infarction. Texture characteristic of ultrasound image is low quality, caused by noise, low frequency and small dimension.

Wavelet extension algorithm is proposed for improving quality of texture result of new image with higher resolution. Aleksandra Mojsilovic *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 description for classification purpose. Gray level co-occurrence matrix, one of the most known texture analysis methods, estimates image properties related to second order statistics. Mari Patrio *et.al.*[14] have used the feature extracted form GLCM with the problem of how to guarantee even quality within a set of rock plates. A.L. Amer *et.al.*[10] proposed a method, namely, the sub-band domain co-occurrence matrix to solved the texture defect detection problem. Therefore, this research proposed a new combines concept of wavelet extension transform with GLCM texture feature were used for diagnosis of myocardial infarction tissue and retrieval in small dimension images

The goal of this paper is to establish the algorithms for texture analysis, which can be detected by texture image as distinguishing a textural normal myocardium from textural infarcted.

This paper is organized as follow. Section 2 introduces background theory of wavelet and co-occurrence matrix. Experimental results are present in section 3, and finally, in section 4, includes the concluding remarks.

2. Methodology

The proposed defect detection and texture retrieval system consist of two stages [10]: (i) The feature extraction part which first utilizes the wavelet extension procedure to decompose textured image into sub-bands and GLCM procedure to computed energy, entropy, contrast and inverse difference moment for each sub-bands (ii) The detection part (texture classification) which is a mahalanobis distance classifier being trained by defect free samples (see fig.1).

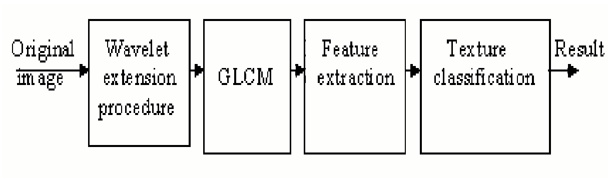


Figure 1: Block diagram

A. Review of 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]:

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

where j and k are integers.

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 $\varphi(t)$. $\varphi(t)$ can be expressed in term of weighted sum of shifted $\varphi(2t)$ as [3]:

$$\varphi(t) = \sqrt{2}\sum_{k} h(k)\,\varphi(2t - k)$$
(2)

where *h(k)'s* are the scaling function (lowpass) coefficients and the mother wavelet $\psi(t)$ is related to the scaling function via

$$\psi(t) = \sqrt{2}\sum_{n} g(k)\,\varphi(2t - k)$$
(3)

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

$$g(k) = (-1)^{k}\,h(1 - k)$$
(4)

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

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.

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

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 2 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.

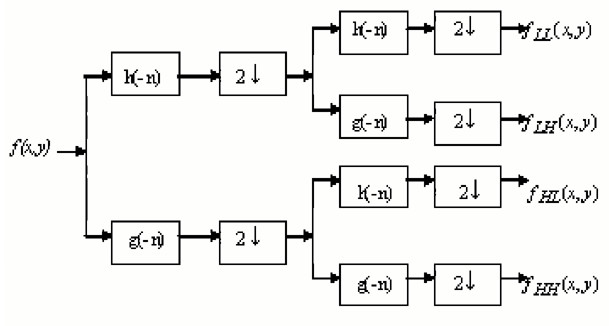
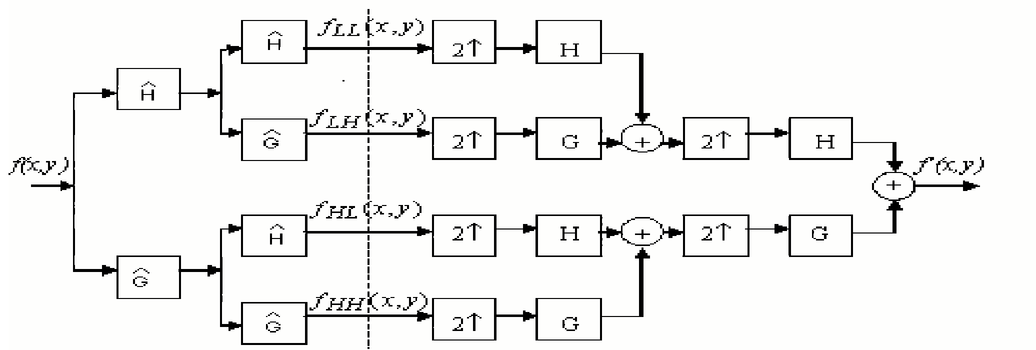
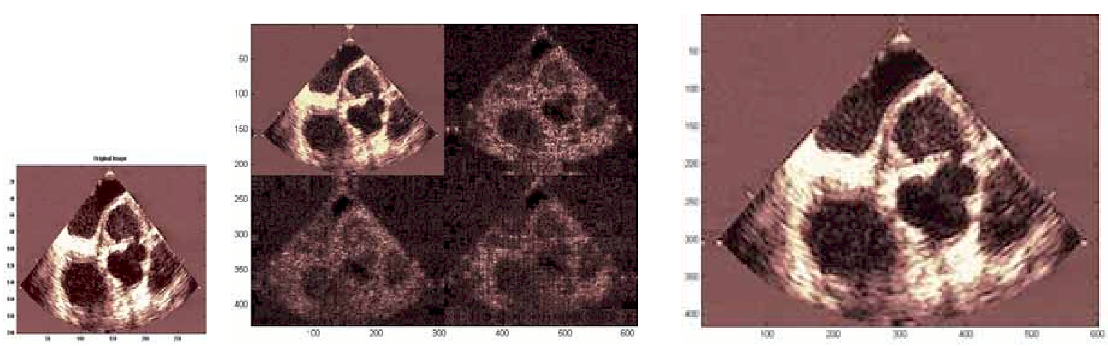


Figure 2: One stage in multiresolution image decomposition



(a) (b)

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



(a) (b) (c)

Figure 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.

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.

B. Review of 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

$$ENT = \sum_i \sum_j p(i,j) \log p(i,j) \quad (5)$$

2). Contrast

$$CON = \sum_i \sum_j (i \quad j)^2 \, p(i,j) \quad (6)$$

3). Angular Second Moment

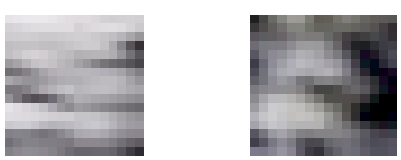
$$ASM = \sum_i \sum_j \{ p(i,j) \}^2 \quad (7)$$

4). Inverse Difference Moment

$$IDM = \sum_i \sum_j \frac{1}{1+(i \quad j)^2} \, p(i,j) \quad (8)$$

In Equation (5) – (8), *p(i,j)* refers to the normalized entry of the co-occurrence matrices. That is

$$p(i,j) = \frac{p_d(i,j)}{R} \quad (9)$$



(a) (b)

Figure 6: a. Normal myocardium zone (16x16), b. Infarcted myocardium zone (16x16).

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. Experimental results

The experiments in this part are used texture image from ultrasound images taken from 15 patients, obtained from clinical hospital. For each patient to be analyzed, five tissue samples are taken from ultrasound image segments corresponding to area not affected (2) by infarction, and five tissue samples taken from image segments corresponding to the infracted (1) area of myocardium.

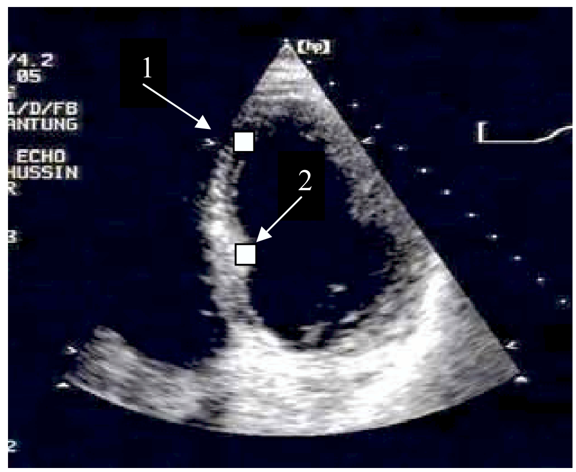
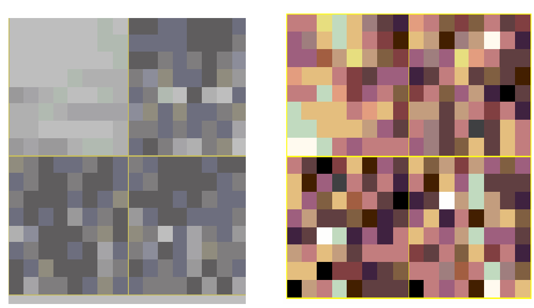
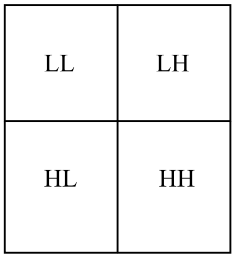


Figure 5: A typical ultrasound image of a human heart. The black square correspond to texture sample taken from a normal area (2) and an indicated infarcted area of myocardium (1).



(a) (b)



(c)

Figure 7: a. Wavelet decomposition of normal myocardium, b. infracted myocardium, and c. the arrangement of the four subbands (LL is low-frequency content of the original picture, LH gives the horizontal high frequencies, HL corresponds to vertical high frequencies and HH the high frequencies in both directions).

TABLE 1: Distance value (D) between normal and infracted zones, Threshold value α = 2.7461.

Patient	D
Infarcted Group	
P1	3.15040
P2	3.02680
P3	3.74600
P4	4.49660
P5	2.81280
P6	2.87220
P7	2.75430
P8	3.88320
P9	3.09640
P10	4.18970
Normal Group	
P11	0.49733
P12	0.98083
P13	1.06870
P14	1.71170
P15	0.39482

4. Conclusions

The following conclusions can be drawn from our studies:

1). Algorithm for texture analysis has advantage for detect difference image from echocardiography as normal myocardium and myocardium infarction.

2). Wavelet extension and co-occurrence matrix procedure approach is an effective method for application in similarity evaluation of texture images.

References

[1]. S.G.Mallat, “A Theory for Multiresolution Signal Decomposition: The Wavelet Representation.” IEEE Trans. on Pattern Analysis and Machine Inteligence, vol. 11, no. 7, pp.674-693, July 1989.

[2]. S.G.Mallat, “Multifrequency Channel Decomposition of Images and Wavelet Models.” IEEE Transaction on Acoustics, Speech and Signal Processing, Vol.37, No.12, December 1989.

[3]. I.Daubechies, “The Wavelet Transform, Time-Frequency Localization and Signal Analysis.” IEEE Trans. on Information Theory, vol. 36, no.5, pp.961-1004, September 1990.

[4]. A.Materka and M.Strzelecki, “Tecture Analysis Methods - A Review,” Technical University of Lodz, Institute of Electronics, COST B11 report, Brussels 1998.

[5]. M.Antonini, M.Barlaud, P.Mathieu, and I.Daubechies, “Image Coding Using Wavelet Transform.” IEEE Trans. on Image Processing, vol. 1, no. 2, pp.205-220, April 1992.

[6]. T.Chang, and C.C.Jay Kuo, “Texture Analysis and Classification with Tree-Structured Wavelet Transform.” IEEE Trans. on Image Processing, vol. 2, no. 4, pp.429-441, October 1993.

[7]. D.Dunn, and W.E. Higgins, “Optimal Gabor Filters for Texture Segmentation.” IEEE Trans. on Image Processing, vol. 4, no. 7, pp.947-964, July 1995.

[8]. Amara Graps, “An Introduction to Wavelet,” IEEE Computational Sciene and Engineering, vol. 2, no. 2, Summer 1995.

[9] A.Mojssilović, M.V.Popović, A .N.Nešković, and A.D.Popović, “Wavelet Image Extension for Analysis and Classification of Infarcted Myocardial Tissue.” IEEE Trans. on Biomedical Engineering, vol. 44, no. 9, pp.856-866, September 1997.

[10]. A.L.Amer, A.Ertüzün, and A.Erçil, “An Efficient Method for Texture Defect Detection: Subband domain Co-Occurrence Matrices.” Image and Vision Computing, Vol.18/6-7, pp.543-553, May 2000.

[11]. Z.Shaohua, “Wavelet-Based Texture Retrieval and Modeling Visual Texture Perception.” Thesis, Department of Electrical Engineering, National University of Singapore, 2000.

[12]. T.Ojala, M.Pietikäinen, and T.Mäenpää, “Multiresolution Gray-Scale and Resolution Invariant Texture Classification with Local Binary Pattern,” IEEE Trans. on Pattern Analysis and Machine Inteligence, vol. 24, no. 7, pp.971-987, July 2002.

[13]. E.Chiu, J.Vaisey and M.S.Atkins, ”Wavelet Based Space-Frequency Compression of Ultrasound Images,” School of Engineering Science, School of Computing Science Simon Fraser University, Burnaby, BC, V5A IS6, Canada, February, 2001.

[14]. M.Partio, B.Cramariuc, M.Gabbouj and A.Visa, “Rock Texture Retrieval using Gray Level Co-occurrence Matrix.” Tempere University of Tecnology, Tempere, Finland.