Neural Network Diagnosis System for 3-Dimensional Ultrasonography with Gabor Filter Aided Speckle Decorrelation

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Abstract

In this paper, a neural network diagnosis system for 3-dimensional ultrasonography using Gabor filters to eliminate the speckle noise is introduced. Since the importance of the relationship between surface features and internal architecture of the breast tumor, we applied our system using three dimensional (3D) inter-pixel correlation instead of 2D features. Furthermore, Gabor filters provide a multi-resolution representation of texture, which increasing the capabilities of ultrasound technology in the differential diagnosis of solid breast tumors. Our experiments show that the performance of the proposed diagnostic method is effective.

1. Introduction

The ultrasound (US) imaging system is widely used in hospitals, physicians’ offices and clinics. Since the traditional 2D ultrasound (2DUS) can’t easily simultaneously demonstrate the surface features and internal architecture of a tumor, the 3D ultrasound (3DUS) has been developed. The physician can now view the construction in 3D [1]-[4]. A 3D object, such as a breast tumor, usually has volume and appears as an uneven complex shape. In 2DUS, if the 2D probe is not located at the correct location or the scanned 2D image contains only partial tumor features, it may result in a misdiagnosis. Because the 3DUS reduces the variability, it could be a potentially reliable diagnostic tool for solid breast tumors. The pixel relation analysis techniques are useful in diagnosing breast lesions. Besides, only one single 2D data slice was used for each case in the conventional 2DUS diagnostic system. When the diagnostic features come from only one slice, that slice may fail to represent all of the tumor’s diagnostic features. For these reasons, 3DUS datasets are used in this paper.

Texture analysis is essential to distinguish a speckled noise from meaningful tissue texture which produced by US imaging [5]. Texture analysis algorithm ranges from random field models to multi-resolution filtering techniques. We propose a multi-resolution representation method based on the Gabor filters. Gabor filters have been used in several image analysis applications including texture classification and segmentation [6]-[7], image recognition [8]-[10], image registration and motion tracking [11]. Most of these researches are related to texture segmentation and analysis. In the paper, Gabor filters are used to extract textured image features using various factors, which improve image resolution, orientation selectivity and spatial frequency tuning, and it can achieve optimal resolution in both space and spatial frequency as well. Using the appropriate filters at the optimal parameters which is user determine increases computational efficiency and extracts more meaningful information. We propose using the texture parameters to compute the auto-correlation matrix, which is used as the characteristic vector in our artificial neural network diagnosis models as well. The region of interest (ROI) and volume of interest (VOI) of the US images are located by physicians.

2. Materials and Methods

2.1 Speckle Noise

The speckle is a type of noise that changes the tissue parameters. It is a phenomenon caused when a coherent imaging system, such as US, is used to image a surface that is rough on the wavelength scale used. The surface produces many reflections in each resolution cell that add constructively or destructively...
to produce the speckled pattern. An US speckled image has the magnitude of a complex Gaussian field with independent real and imaginary parts that are distributed identically [12].

A small amount of additive noise might be shown in US scans. An image may be classified as possessing Gaussian noise with a very small standard deviation into different levels of speckled noise. The p(x) (Zero-mean Gaussian noise which also represents the speckle noise) with standard deviation σ is drawn from the probability density function

\[ p(x) = \frac{1}{\sqrt{2\pi} \sigma} \exp\left(-\frac{x^2}{2\sigma^2}\right) \]  

where \( x \) denotes the gray level of the uncorrupted image [13].

### 2.2 Gabor Filters

2-D Gabor function is a Gaussian modulated by a complex sinusoidal plane wave of some frequency and orientation. The general form for the 2-D Gabor function is given by

\[ G(x, y) = g(x, y) \cdot \exp[2\pi(i(Ux + Vy))] \]  

where \( i = \sqrt{-1}, U = F \cos \theta, V = F \sin \theta, \) and \( F=1/T \) (T is period), \( g(x, y) \) is a 2-D Gaussian function given by

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

with \( \sigma \) is standard deviation. From Eq. (2) and (3), and by applying the Euler identity, Eq. (2) can be rewritten as [14]

\[ G(x, y) = \frac{1}{2\pi \sigma_x \sigma_y} \exp\left(-\frac{x^2 + y^2}{2\sigma_x \sigma_y}\right) \cdot \{\cos[2\pi(Ux + Vy)] + i \sin[2\pi(Ux + Vy)]\} \]  

Because Gabor filters are used to extract meaningful features from real images, the response to the even-symmetrical filter components will remain unchanged for filters oriented 180° out of phase and the odd-symmetrical component will be negated [15]. Therefore, our proposed Gabor function representation uses only real-valued, even symmetrical filters oriented over a 180° range as opposed to the full 360° range commonly described in the literature. Gabor Filters can filter the unnecessary speckle noise and increase the accuracy measured with the angle, because that different laminations of the tumor contain different US images.

### 2.3 Auto-correlation Function

The correlation between neighboring pixels within the 3D images is a patent feature of a tumor. The normalized auto-correlation coefficients [16] are used to reflect the inter-pixel correlation within an image.

The 3D normalized auto-correlation coefficients can be defined as

\[ r(\Delta m, \Delta n, \Delta p) = \frac{A(\Delta m, \Delta n, \Delta p)}{\Delta(0,0,\Delta)} \]  

where

\[ A(\Delta m, \Delta n, \Delta p) = \frac{1}{(M-\Delta m)(N-\Delta n)(P-\Delta p)} \sum_{x=0}^{M-\Delta m} \sum_{y=0}^{N-\Delta n} \sum_{z=0}^{P-\Delta p} f(x, y, z) \]  

where \( r(\Delta m, \Delta n, \Delta p) \) is the normalized auto-correlation coefficient between pixel \((x,y,z)\) and pixel \((x+\Delta m,y+\Delta n,z+\Delta p)\) in an image with size \( M \times N \times P \).

To generate similar auto-correlation features for images with different brightness but with a similar pixel relation, the auto-correlation coefficients are further modified into mean-removed auto-covariance coefficients. This auto-covariance is expressed as

\[ r'(\Delta m, \Delta n, \Delta p) = \frac{A'(\Delta m, \Delta n, \Delta p)}{A'(0,0,\Delta)} \]  

where

\[ A'(\Delta m, \Delta n, \Delta p) = \frac{1}{(M-\Delta m)(N-\Delta n)(P-\Delta p)} \sum_{x=0}^{M-\Delta m} \sum_{y=0}^{N-\Delta n} \sum_{z=0}^{P-\Delta p} f(x, y, z) - \bar{f} \]  

where \( \bar{f} \) is the mean value of \( f(x,y,z) \). The absolute value is adopted in the above equation because a negative value may be produced. In this study, these 3D auto-covariance coefficients for each breast tumor US image are found and used as inter-pixel pixel relation features to distinguish the differences between benign and malignant tumors.

### 2.4 Neural Networks

Neural networks have been applied in the image processing field to solve classification, recognition, prediction or compression problems. Neural networks consist of simple computing units, called neurons or processing units, and the massive interconnections between these units.

A neuron is the fundamental computing unit of a neural network. Figure 1 shows the basic neuron structure.

In Figure 1, each neuron has many input signals \( x_1, x_2, \cdots, x_n \) and one output signal \( y \).

![Figure 1. The basic structure of a neuron.](image-url)
The relational input and output signal function is expressed as

\[ y(t) = f \left( \sum_{i=1}^{n} \omega_i \cdot x_i(t) \right) \tag{9} \]

where \( \omega \) is synaptic weights, \( t \) is time and \( n \) is the number of input node. The activation function \( f(x) \) is written as

\[ f(x) = \frac{1}{1 + e^{(-x)}} \tag{10} \]

We used the feed-forward neural network in this research. These components are valid whether the neuron is used for input, output, or is in one of the hidden layers. Neurons are organized into layers, called neuron layers, and the neuron layers would constitute neural networks. Figure 2 shows a feed-forward neural network example with three neuron layers (one input layer, one output layer and one hidden layer).

![Figure 2. A feed-forward neural network with three neuron layers.](image)

3. Experiments and Results

The 3DUS imaging was performed using a Voluson 530 (Kretz Technik, Zipf, Austria) scanner and a Voluson small part transducer S-VNW5 to 10. The transducer, which is a linear-array transducer with a frequency of 5 to 10 MHz, a scan width of 40 mm (switchable in 3-mm steps) and a sweep angle of 20 to 25°, allows a 3-D volume scan. Figure 3 is the 2D image planes arranged in a fanlike geometry.

![Figure 3. A fanlike geometry.](image)

Figure 4 shows three fixed axes three 2D datasets for 3DUS.

![Figure 4. Three datasets of 2D.](image)

These three 2D datasets are used for the Gabor filter process. We used the auto-correlation to extract the required information. This information is used as the input signal for the neural network. Figure 5 shows the overall procedure.

![Figure 5. The overall procedure.](image)

Figure 6 shows that the speckled noise has apparently been reduced. A 3DUS image combined using a series of 2D slices will therefore be improved.

![Figure 6. (a) is the original 2D ultrasound image and (b) is the 2D ultrasound image after the processor of Gabor filters.](image)

The overall process performance was evaluated using 48 malignant and 100 benign tumour cases. Table 1 lists the number of training iterations for each training set.

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<th>Number of Malignant Cases</th>
<th>Number of Benign Cases</th>
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