International Journal of Information Technology and Knowledge Management
July-December 2009, Volume 2, No. 2, pp. 445-448

IDENTIFICATION OF MICROCALCIFICATION IN MAMMOGRAPHIC IMAGES USING WAVELET AND ARTIFICIAL NEURAL NETWORKS

K. Prabhushetty[*] & Dr. V. R. Udupi[**]

This paper takes digital mammograph for scrutiny with the angle of finding the microcalcification in the mammographic images through the help of artificial neural networks (ANN) and wavelet-based sub band image decomposition. When the mammographs are digitized the micro calcification present in it will be in the form of high frequency component of the image matrix. In order to detect it we filter the image using Hessian filter and apply DWT and finding the Skewness and Kurtosis of the resulting image, before applying the BPN algorithm for diagnosing the cancer. The neural network contains one input, two hidden and one output layers. The described method has been tested on many mammographic images taken from the Digital Database for Screening Mammography (DDSM).

Keywords*:* Kurtosis, Wavelet Transform, Breast, Cancer, Malignant, Skewness.

1. Introduction

Women suffering from Breast cancer have been taken as a serious concern all around the world, As it directly affects the next generation to come. Mammography has become a major field in medical diagnostics as there are one out of eight women affected by breast cancer. Constant Mammographic screening programs for women of a particular age group are taking place worldwide. In the developing and the developed world breast has become the major threat for the lives of the women. WHO (World Health Organization) estimates that nearly 2,00,000 women worldwide die of breast cancer each year. Breast cancer is one among the top three cancers in World involving women. In United States, the American Cancer Society estimates that, 215 990 new cases of breast cancer has been diagnosed. It is the leading cause of death due to cancer in women under the age of 65. In India, breast cancer accounts for 23% of all the female cancers followed by cervical cancers (17.5%) in metropolitan cities such as Mumbai, Calcutta, and Bangalore [1]. For detecting the Breast cancer a high quality image is required. Clinicians who diagnose the microcalcification must be trained very well in order to attain the correct diagnosis. Detected Macro-calcifications will be often benign (not cancer).

The benign Micro-calcification will be large and round in the mammograph. Smaller and more numerous than the larger macro-calcifications will also be present as a microcalcification. They seldom will be detected as the cancer complaint. The radiologist will look at the size, shape and distribution of the micro-calcifications to see if they are suspicious. An ultrasound study and a biopsy and lot of mammograms may be necessary. Suspicious micro-calcifications turn out to be cancer about 20 to 25 percent of the time.

It is very hard to diagnose whether it is a cancer or not. They are called Indeterminate. When this happens the clinicians may take more X-rays to help decide if the micro-calcifications are benign, probably benign, suspicious, or malignant. If they are probably benign, then there is a 98 percent chance that they are not cancer. However, if they are suspicious, more follow-up is needed.

2. Implementation

Mammographic image is initially made to be convoluted with the Hessian matrix to smoothen and filter it. The filtered images are more bound to have higher detection ratio than the one without filtering [1].

Hessian matrix is a gradient method of filtering the image. The Hessian matrix is the square matrix of second-order partial derivatives of a function; that is, it describes the local curvature of a function of many variables. The Hessian matrix was developed in the 19th century by the German mathematician Ludwig Otto Hesse and later named after him. Hesse himself had used the term "functional determinants".

Given the real-valued function

$$f(x_1, x_2, x_3, \ldots\ldots x_{n)} \quad (1)$$

If all second partial derivatives of f exist, then the Hessian matrix of f is the matrix

$$H(f)_{ij}(x) = D_i D_j f(x) \quad (2)$$

Where $x = (x_1, x_2, ..., x_n)$ and D_i is the differentiation operator with respect to the ith argument. Hessian matrices

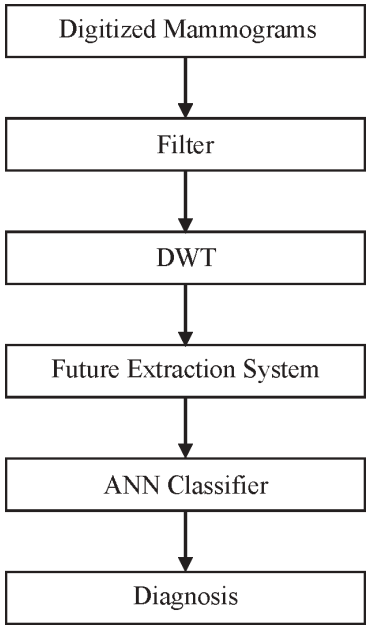
[*] Department of E&C, K.L.E Engineering College, Belgaum, Karnataka, India. *Email: k_prabhushetty@rediffmail.com*
[**] Maratha Mandal Engineering College, Belgaum, Karnataka India *E-mail: vishwa_u@yahoo.com*

are used in large-scale optimization problems within Newton-type methods because they are the coefficient of the quadratic term of a local Taylor expansion of a function. That is,

$$Y = f(x + \Delta x) \sim f(x) + J(x)\Delta x + 1/2\Delta x^T H(x)\Delta x \qquad (3)$$

where J is the Jacobian matrix, which is a vector (the gradient) for scalar-valued functions. The full Hessian matrix can be difficult to compute in practice; in such situations, quasi-Newton algorithms have been developed that use approximations to the Hessian. The most well-known quasi-Newton algorithm is the BFGS algorithm.

MICROCALCIFICATION DETECTION



3. CLASSIFICATION

Skewness: Skewness, the third standardized moment, is written as γ_1 and defined as $\gamma_1 = \mu_3/\sigma^3$ where μ_3 is the third moment about the mean and σ is the standard deviation. Equivalently, skewness can be defined as the ratio of the third cumulate κ_3 and the third power of the square root of the second cumulant. This is analogous to the definition of kurtosis, which is expressed as the fourth cumulant divided by the fourth power of the square root of the second cumulant.

For a sample of n values the *sample skewness* is

$$g1 = \frac{k_3}{k_2^{3/2}}$$

$$g1 = \frac{\sqrt{n\sum_{i=1}^{n}(x_i - x)^3}}{\left(\sum_{i=1}^{n}(x_i - x)^2\right)^{3/2}}$$

where X_i is the i^{th} value, X is the sample mean, m_3 is the sample third central moment, and m_2 is the sample variance. Given samples from a population, the equation for the sample skewness g_1 above is a biased estimator of the population skewness. The usual estimator of skewness is

$$g1 = \frac{k_3}{k_2^{3/2}}$$

$$G1 = \frac{\sqrt{n(n-1)g_1}}{n-2}$$

where k_3 is the unique symmetric unbiased estimator of the third cumulant and k_2 is the symmetric unbiased estimator of the second cumulant. Unfortunately G_1 is, nevertheless, generally biased. Its expected value can even have the opposite sign from the true skewness.

The skewness of a random variable X is sometimes denoted Skew [X]. If Y is the sum of n independent random variables, all with the same distribution as X, then it can be shown that Skew [Y] = Skew [X] / $\sqrt{n}$.

Skewness has benefits in many areas. Many simplistic models assume normal distribution i.e. data is symmetric about the mean. The normal distribution has a skewness of zero. But in reality, data points are not perfectly symmetric. So, an understanding of the skewness of the dataset indicates whether deviations from the mean are going to be positive or negative.

KURTOSIS

Kurtosis, The fourth standardized moment is defined as

$$\frac{\mu_4}{\sigma^4}$$

where μ_4 is the fourth moment about the mean and σ is the standard deviation. This is sometimes used as the definition of kurtosis in older works, but is not the definition used here.

Kurtosis is more commonly defined as the fourth cumulate divided by the square of the variance of the probability distribution,

$$\gamma = \frac{k_4}{k_2^3}$$

$$\gamma = \frac{\mu_4}{\sigma^4 - 3}$$

which is known as **excess kurtosis**. The "minus 3" at the end of this formula is often explained as a correction to make the kurtosis of the normal distribution equal to zero. Another reason can be seen by looking at the formula for the kurtosis of the sum of random variables. Because of the use of the cumulant, if Y is the sum of n independent random variables,

all with the same distribution as X, then Kurt [Y] = Kurt [X] / n, while the formula would be more complicated if kurtosis were defined as μ_4 / σ^4.

More generally, if X_1, ..., X_n are independent random variables all having the same variance, then

$$Kurt\left(\sum_{i=1}^{n} X_i\right) = 1/n^2 \sum_{i=1}^{nn} Kurt(X_i)$$

Whereas this identity would not hold if the definition did not include the subtraction of 3. The fourth standardized moment must be at least 1, so the excess kurtosis must be –2 or more; there is no upper limit and it may be infinite.

Back Propogation Algorithm

The back propagation algorithm is similar to the steepest descent algorithm with the difference that the step length μ is kept fixed during the training. Hence the back propagation algorithm is obtained by choosing $R = I$ in the parameter. The step length is set with the option Step Length, which has default = 0.1.

The training algorithm in may be augmented by using a momentum parameter, which may be set with the Momentum option. Note that the default value of momentum parameter is 0. The idea of using momentum is motivated by the need to escape from local minima, which may be effective in certain problems. In general, however, the recommendation is to use one of the other, better, training algorithms and repeat the training a couple of times from different initial parameter initializations. The simulation is carried out by using the following conditions.

1) Test mammogram images were obtained by scanned as raw format with 8-bit grayscale and 256 × 256 pixels size. These mammograms have been chosen by the radiologist and suspected as mammograms with micro calcification. In this simulation, 30 variation of image as part of 18 digitized mammograms is used.

2) The chosen wavelet basis function is the Daubechies with four coefficients as a filter banks. These processes were applied without 2-factor down sampling from wavelet transforms coefficients. It's used to reduce lost information and maintain size of images.

3) Global image enhancement procedure was applied only on 4-level decomposed detail sub band image (high pass components) using multiscale adaptive gain method. In this technique, high pass components will be suppressed if it's value less than the threshold and will be increased if it's greater than threshold. Finally the back propagation algorithm was used to classify the image as either benign or malign.

5. RESULTS AND DISCUSSION

The described method has been tested on many mammographic images taken from the Digital Database for Screening Mammography (DDSM). The primary purpose of this database is to facilitate a sound research in the development of computer algorithms to aid in screening.

In particular, all the microcalcifications identified by the specialists in the database (many of them classified with a very high subtlety rating) have been correctly enhanced by the algorithm without the introduction of any artifact, allowing a more simple detection by the radiologist with respect to the plain image or the image processed by standard algorithms.

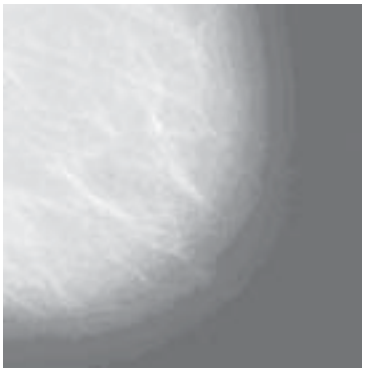


Figure 1: Shows the Region of Interest (ROI) of an Original Dense Mammographic Image with a Microcalcification Lesion

Figure 2: Shows the Wavelet Transformed Image

6. CONCLUSION

The regions of clustered microcalcification can be detected and the presence another location of clustered microcalcification could be considered to clarify the diagnoses. In order to test the detection method, we used the visual analysis to detect presence microcalcification in mammograms based on comparison between the result images and the original ones. The result of test images shown effectiveness simulation on microcalcification detection, even there are some result could not detect the clustered microcalcification. Fail of detection process will reduce the calculation of Simulation effectiveness. From the 50 test

images, there were the 48 test images result a good detection process and just two images failed. Additionally the processing is simple and does not require a full decomposition and reconstruction.

REFERENCE

[1] R. N. Strickland and H. I. Hahn, "Wavelet Transform for Detecting Microcalcification in Mammograms", *IEEE Transaction on Medical Imaging,* **15**(2) (1996) 218-229.

[2] H. Yoshida, K. Doi, R. M. Nishikawa, "Automated Detection of Clustered Microcalcification in Digital Mammograms using Wavelet Transform Techniques", *Proc. SPIE,* **21**(67) (1994) 868-886.

[3] M. N. Gurcan, Y. Yardimci, A. E. Cetin and R. Ansari, *"Automated Detection and Enhancement of Microcalcification on Digital Mammograms using Wavelet Transform Techniques"*, Dept. of Radiology, Univ. of Chicago (1997).

[4] S. Mallat, "A Theory for Multiresolution Signal Decomposition: The Wavelet Representation", *IEEE Trans. Pattern. Annal. Machine Intell.*

[5] I. Daubechies, "Orthonormal Bases of Compactly Supported Wavelet", *Comm. on Pure and Applied Mathematics,* **41**.

[6] A. F. Laine, S. Schuler, J. Fan and W. Huda, "Mammographic Feature Enhancement by Multiscale Analysis", IEEE *Transaction on Medical Imaging,* **13**(4) (1994) 725-740.

[7] Y. Barnett, T. Lewis, *"Outliers in Statistical Data"*, 3w Ed. New York: John Wiley & Sons, 1994. **11**(7) 674-693, (1989) 906-966, (1988) 697.