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Research Paper

DIGITAL MAMMOGRAMS CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK BASED ON BIDIMENSIONAL EMPIRICAL MODE DECOMPOSITION FEATURES

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This paper presents an efficient feature extraction technique, i.e., Bidimensional Empirical Mode Decomposition (BEMD) for mammogram images. The EMD approach is fully adaptive and data driven, proved reliable for monodimensional signals. BEMD is used to extract features at numerous scales or spatial frequencies. Five statistical textural features had been extracted from preprocessed digital mammograms by using BEMD. These features are mean, standard deviation, kurtosis, skewness and entropy. Artificial Neural Network (ANN) was employed to distinguish mass and non mass tissue based on these features. An accuracy of 92.5%, sensitivity of 87.5% and specificity of 96.55% was obtained by proposed method which is better than other methods.

Keywords: BEMD, ANN, Region of Interest (ROI), Classification, Feature extraction

INTRODUCTION

American Medical Association, The American College of Obstetricians and Gynecologists, the American Cancer Society, the National Cancer Institute and National comprehensive Cancer Network all have issued guidelines saying that the all women should be eligible for screening mammograms starting at age 40 (htttp://www.breastcancer.org). Mammography is the most powerful breast cancer detection tool. Mass and microcalcification are two confusing features present in a mammogram. Masses are identified by their shape and margin characteristics. Microcalcifications are small calcium deposit and appear as a group of bright spots in mammogram (Herwanto *et al.*, 2013). In literature many feature extraction techniques like GLCM, wavelet have been used for mammogram classification. This

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paper introduces a new feature extraction technique, i.e., BEMD. The EMD is a multi-resolution decomposition that performs a joint space-spatial frequency representation of the signal (Huang *et al.*, 1998). It is adaptive, fully data driven method, and is suitable for non-linear and non-stationary data analysis (Nunes *et al.*, 2003). BEMD is applying EMD for texture extraction and image filtering, which are generally known as a difficult and challenging computer vision problem.

This paper is organized in the following sections, section II presents BEMD algorithm, methodology is given in section III, experimental results are shown in section IV and section V concludes the paper.

BIDIMENSIONAL EMPIRICAL MODE DECOMPOSITION METHOD

According to basic concept of EMD, BEMD uses the steps as described in this section.

Step 1: Read the input data image, $I(x, y)$. Initialize $h(x, y) = I(x, y)$.

Step 2: Find all the extrema points in data.

Step 3: By using surface interpolation join all the maximum points for obtaining the upper envelope $U(x, y)$ and join all the minimum points for getting the lower envelope $L(x, y)$.

Step 4: Find out the average value $m(x, y)$ of upper and lower envelope as given in "(1)",

$$m(x) = \frac{[U(x,y) + L(x,y)]}{2} \qquad ...(1)$$

Step 5: Subtract this average value from $h(x, y)$ as shown in "(2)", and chec *k* whether the obtained value $h(x, y)$ satisfies the condition of an IMF or not.

$$h(x,y) = h(x,y) - m(x,y) \qquad ...(2)$$

The first condition for an IMF is that in the whole data set, the number of extrema and the number of zero-crossings must either be equal or differ at most by one. Second condition is that at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

Step 6: (a) If $h(x, y)$ is not an IMF then , treat it as an original data and repeat steps 1 to 5 until the first IMF is found. Process of finding an IMF is known as sifting process. Stopping criteria of this sifting process, a value of SD as given in "(3)", is chosen between 0.2 and 0.3.

$$SD = \frac{\sum_{x=0}^{X}\sum_{y=o}^{Y}\left|h_{k-1}(x,y) - h_k(x,y)\right|^2}{\sum_{x=0}^{X}\sum_{y=0}^{Y}h^2{}_{k-1}(x,y)} \qquad ...(3)$$

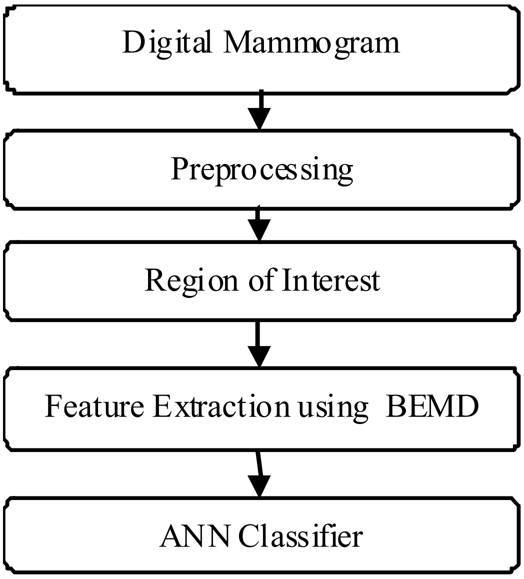
Step 6: (b) If $h(x, y)$ satisfies the condition of IMF then it is first IMF. IMF1 = $h(x, y)$ and then $r(x, y) = I(x, y) - IMF_1$. Check whether $r(x, y)$ is monotonic or not. If it is monotonic then it is a residue, no more IMF can be extracted and if it is not a residue treat it as an original signal and repeat all the steps discussed above. After finding all the IMFs if we superimpose them and add residue in that we get the original data as in "(4)", where n is total number of IMFs.

$$I(x,y) = \sum_{j=1}^{n} IMF_n + r(x,y) \qquad ...(4)$$

METHODOLOGY

In this section steps used for classification of digital mammograms as masses and non masses has been discussed. Figure 1 shows the flowchart of proposed method.

Figure 1: Flow Chart for Proposed Method



Digital Mammogram

Database used in this paper is taken from Mammographic Image Analysis Society (MIAS) (http://peipa.essex.ac.uk/info/mias.html). The MIAS data consist of 207 images of normal breast, 64 benign and 51 malignant. 85 mammograms of MIAS data have mass, and 25 mammograms have microcalcification. Size of all images is 1024 x1024 and approximate radius (in pixels) of a circle enclosing the abnormality is given.

Pre-Processing

Contrast-Limited Adaptive Histogram Equalization (CLAHE) has been used for enhancing the contrast of mammogram image. CLAHE operates on small regions (or tiles) in the image rather than the entire image. Contrast of each tile is improved, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. Using bilinear interpolation the neighboring tiles are then combined to eliminate artificially induced boundaries. The contrast, particularly in homogeneous areas, can be limited to avoid amplifying noise that may be present in the image (www.mathworks.com).

Region of Interest Extraction

In this section two types of digital mammogram that are normal and having masses have been chosen. On the basis of given information, i.e., radius and centre of abnormality in MIAS database suspicious regions have been extracted as ROIs. A window of 40 x 40 has been taken for ROI. Total 53 ROIs were selected including 29 negative (normal tissue) and 24 positive ROIs (mass tissue).

Feature Extraction using BEMD

BEMD was performed on preprocessed ROIs and two IMFs were obtained for each image, then five statistical features had been extracted from these coefficients. These features are mean, standard deviation, kurtosis, skewness and entropy. Two IMFs were used for extracting features.

Artificial Neural Network classifier

Neural networks are composed of simple elements operating in parallel. These elements are motivated by biological nervous systems. The connections between elements determine the network function. Neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Neural networks are trained or adjusted, so that a particular input leads to a specific target output. The network is adjusted, based on an evaluation of the output and the target, until the output matches the target. Neural networks have been trained to perform functions in various fields, including identification, classification, pattern recognition, speech, vision and control systems. Neural networks can also be taught to solve problems that are difficult for conventional computers or human beings. In this paper pattern recognition network was used. These are feed forward networks that can be trained to classify inputs according to target classes. For pattern recognition networks the target data should consist of vectors of all zero values except for a 1 in element *i*, where *i* is the class they are to stand for.

EXPERIMENTAL RESULT

The ANN classifier was used for classification of mass and non mass tissue. Pattern recognition network was used and scaled conjugate gradient backpropagation was used as training function. Table 1 shows the confusion matrix of classification. The performance matrices such as accuracy, sensitivity and specificity had been calculated using "(5)", "(6)" and "(7)" respectively. An accuracy of 92.5%, a sensitivity of 87.5% and specificity of 96.55% had been obtained in this paper, as shown in Table 2. The numer of neurons used is 7 for getting an accuracy of 92.5%. In literature Anitha *et al.* (2012) proposed classification of mass and non mass using SVM classifier based on wavelet features. In this section classification comparison of proposed BEMD features using ANN with wavelet transform features using SVM is also shown in Table 3.

Table 1: Confusion Matrix

Actual Class	Predicted Class	
	Non Mass	Mass
Non Mass	28	2
Mass	1	22

Table 2: Performance Analysis of Proposed Method

Performance Metrics	Analysis
Accuracy	92.5%
Sensitivity	87.5%
Specificity	96.55%

Table 3: Comparison of Proposed Method with Wavelet Transform Features

Performance Metrics	Reference Method (Wavelet Features + SVM) (Anitha *et al.*, 2012)	Proposed Method (BEMD features + ANN)
Accuracy	89.41%	92.5%
Sensitivity	95.56%	87.5%
Specificity	82.5%	96.55%

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FP} \quad ...(5)$$

$$Sensitivit\,y = \frac{TP}{TP+FN} \quad ...(6)$$

$$Specificity = \frac{TN}{TN+FP} \quad ...(7)$$

CONCLUSION

The main purpose of this paper is to study BEMD features of mammogram images and to classify them as masses and non-masses using ANN pattern recognition method. An accuracy of 92.5%, sensitivity of 87.5% and specificity of 96.55% had been obtained. This paper also provides a comparison with wavelet features, given in Table 3. In future work classification of masses and microcalcification can also be done by using proposed method.

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