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Classification of Mammograms Using Bidimensional Empirical Mode Decomposition Based Features and Artificial Neural Network

Srishti Sondele[1] and Indu Saini[2]

[1]M.Tech Student, Department of Electronics & Communication Engineering
Dr. B. R. Ambedkar, National Institute of Technology,
Jalandhar-144011, Punjab, India
[2]Assistant Professor, Department of Electronics & Communication Engineering
Dr. B. R. Ambedkar, National Institute of Technology,
Jalandhar-144011, Punjab, India

[1]srishti.sondele@gmail.com, [2]indu.saini1@gmail.com

Abstract

This paper, presents a competent feature extraction technique, i.e., Bidimensional Empirical Mode Decomposition (BEMD) for mammogram images. The EMD is fully adaptive and data driven technique. BEMD is used to extract features at numerous scales or spatial frequencies in form of Intrinsic Mode Functions (IMFs). By using these IMFs five statistical textural features i.e., mean, standard deviation, kurtosis, skewness and entropy have been extracted from Region of Interests (ROIs) of preprocessed digital mammograms. Artificial Neural Networks (ANN) which is inspired by biological neurons has been explored to classify mammograms into different classes. Three experiments, i) classification of normal mammogram and calcification, ii) classification of mass tissue and calcification and iii) classification of normal, mass and calcification have been performed. Accuracies of 95.5%, 93.2% and 82.4% have been obtained by proposed method from respective experiments.

Keywords: *BEMD, ANN, ROI (Region of Interest), Classification, Feature Extraction, Mammogram*

1. Introduction

In today's life breast cancer is a severe problem due to environmental causes, diet and lifestyle. Mammography is an effective breast cancer detection tool. Since the number of patients is increasing, there is a need of an automated computer system**.** Many medical institutions have given guidelines saying that the all women should be eligible for screening mammograms starting at age 40 [1]. Mass and Calcifications are two main abnormalities that can be present in a mammogram. Masses are identified by their shape and margin characteristics. Masses are areas that look abnormal and they can be many things, including cysts and solid tumors which are non-cancerous [2]. Cysts can be fluid-filled sacs (simple cysts) or can be somewhat solid (complex cysts). Simple cysts are benign and there is no need of biopsy. Calcifications are small mineral deposits within the breast tissue. They look like minute white spots on a mammogram. They may or may not be cancerous.

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2. Literature Review

In literature many advanced techniques have been used for feature extraction and classification of mammograms. For classification of mammogram mass shapes as round or irregular, Lori Mann Bruce *et al.*, demonstrated the utility of artificial neural networks, in combination with wavelet transforms [6]. Brijesh Verma *et al.*, presented a system based on fuzzy-neural and feature extraction techniques for detecting and diagnosing microcalcifications, patterns in digital mammograms [7]. J. E. Ball *et al.*, presented an approach for detecting and segmenting mammographic mass cores based on ROC AZ value comparison. In this adaptive thresholding was applied to a contrast-enhanced version of the gray-scale mammogram, where the threshold was a function of the localized gray-level mean and variance [8].

Guodong Zhang *et al.*, used an algorithm for MCC and suspicious area detection, which used a predefined small window to scan over the entire digital mammogram. For feature extraction author had modified the formulae for energy, entropy, standard deviation and skew by changing the starting of the iterations from the lowest grey level possible to the first pixel of the image and by ending of the iterations from the highest grey level possible to the final pixel of the image. Then classification had been done into benign and malignant [9]. An Extreme Learning Machine (ELM) classifier had been used by G. Vani *et al.*, to classify the abnormal masses of digitized mammograms into benign and malignant tumors [10].

Viet Dzung Nguyen *et al.*, proposed a detection process based on local contrast thresholding and rule-based classification which was performed over the preprocessed and segmented mammograms [11]. J.C. Nunes *et al.*, presented a texture analysis algorithm based on Gray-Level Cooccurrence (GLC) model and Bidimensional Empirical Mode Decomposition (BEMD) of a texture field [12]. Gabriel Rilling *et al.*, presented, Huang's data-driven technique of Empirical Mode Decomposition (EMD), and issues related to its effective implementation were discussed [13].

M. Vasantha *et al.*, proposed an image classifier to classify the mammogram images. Mammogram image was classified into normal image, benign image and malignant image. Decision tree algorithms were applied to mammography classification [15]. D.M.Garge and V.N. Bapat reported a low cost wavelet based image processing technique [16]. Ayman AbuBaker compared the characteristics of true masses to the falsely detected masses using wavelet decomposition transform combining with SVM [17].

J. Anitha *et al.*, discussed mass detection and classification in mammogram images with the use of features extracted from the mass regions obtained by the automatic morphological based segmentation method [18]. In this approach, the wavelet features were extracted from the detected mass regions and were compared with features extracted using Gray Level Co-occurrence Matrix (GLCM) to differentiate the TP and FP regions. Classifications of the mass regions were carried out through the Support Vector Machine (SVM) to separate the segmented regions into masses and non-masses based on the features. Herwanto *et al.*, applied association technique based on classification algorithm to classify microcalcification and mass in mammogram [19].

J.C. Nunes *et al.*, presented an introduction to the EMD and its extension on bidimensional data. It described implementation details of sifting process, including the extrema detection by morphological reconstruction and the Radial Basis Function (RBF) for surface interpolation [20]. Based on above literature, this work introduces a new feature extraction technique for mammograms, *i.e.*, BEMD. The EMD is a multi-resolution decomposition. It is adaptive, fully data driven method, and is suitable for non-linear and non-stationary data analysis. BEMD is, applying EMD to texture extraction and image filtering, which are recognized as difficult in computer vision problem [20]. In author's previous work [21] classification of non mass and mass had been done.

This paper is organized in the following sections, Section 1 presents introduction, Section 2 deals with literature review, section 3 discusses BEMD algorithm, methodology is given in Section 4, experimental results have been shown in Section 5 and Section 6 concludes the paper. Figure 1 and Figure 2 show the example of mammogram having mass and calcification respectively.

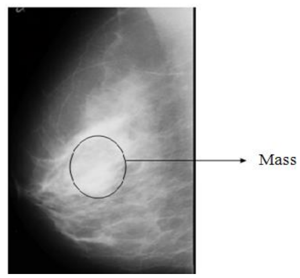

Figure 1. Mammogram having Mass (From MIAS)

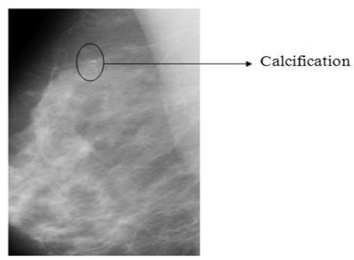

Figure 2. Mammogram having Calcification (From MIAS)

3. Overview of Bidimensional Empirical Mode Decomposition Method

EMD is a method which decomposes any compound data set into a finite and often small number of components, known as intrinsic mode functions (IMF). It can be applied to non linear and non stationary data analysis. When EMD is used for image texture analysis then it is known as BEMD. 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 out all the extrema points in data.

Step 3) With the help of 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)",

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

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

$$h(x,y) = h(x,y) - m(x,y) \tag{2}$$

The first condition for an IMF is that the total number of extrema and the number of zero-crossings must either be equal or differ at most by one. Second condition is that at each 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. A stopping criterion of this sifting process, a value of SD as given in "(3)", is chosen between 0.2 and 0.3.

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

Step 6) *(b)* If h(x,y) satisfies the condition of IMF then it is first IMF. IMF_1=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.

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

4. Methodology

This section, discusses the methodology which has been used for the proposed work. Database has been taken from Mammographic Image Analysis Society (MIAS) for this work [3]. Each step used in this work, has been explained in detail.

4.1. Digital Mammogram Database

This database consists of total 322 images, including 207 normal and 115 diseased images. It also provides information about images. First column of MIAS database gives reference number, second column gives character of background tissue(Fatty, Fatty-glandular, Dense-glandular), third column discusses class of abnormality present(Calcification, Well-defined/circumscribed masses, Spiculated masses, ill-defined mass, Architectural distortion, Asymmetry, Normal), fourth column notifies severity of abnormality (Benign, Malignant). Fifth and sixth columns provides x, y image-coordinates of centre of abnormality and seventh column denotes approximate radius (in pixels) of a circle enclosing the abnormality is given in respectively [3].

4.2. Pre-processing

As mammograms are medical images, it is tough to interpret them [13]. So there is a need of preprocessing to increase the quality of mammograms. In this paper, 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 uniform distribution or Rayleigh distribution or exponential 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 [4].

4.3. Region of Interest Selection

Region of interest is a subset of samples selected from a database which is taken for a particular application. In a medical image ROI is a boundary of a suspicious region. In this section, three types of digital mammogram i.e. normal, having masses and having calcification had been chosen. On the basis of information (*i.e.,* radius and centre of abnormality *etc*) given in MIAS database, suspicious regions had been manually extracted as ROIs. A window of 40x40 has been taken for ROI. For first classification total 67 ROIs (including 50 normal and 17 calcification) had been selected, for second classification total 73 ROIs (including 56 mass tissues and 17 calcifications) had been selected and for third classification total 102 ROIs (including 29 normal, 56 mass tissues and 17 calcifications) had been selected.

4.4. Feature Extraction using BEMD

Feature extraction is an integral part of classification. This helps in distinguishing the database of different classes and also enhances the accuracy of classifier. In this paper for extraction of features, BEMD has been performed on preprocessed ROIs of mammograms and two IMFs have been obtained for each ROI. Since, IMFs are two dimensional matrices (size of each IMF is 40x40); the size of feature vector for all images will be very large. This will make ANN very complicated and computation time will also increase. In order to reduce the size of feature vector, five statistical parameters, *i.e.,* mean, standard deviation, skewness, kurtosis and entropy had been extracted from these coefficients.

4.5. ANN Classifier

For classifying samples of a database which are associated with different classes, we need a classifier. Artificial Neural networks are composed of simple elements operating in parallel. These elements are motivated by biological nervous systems. Neural network can be trained to perform a particular function by adjusting the values of the connections between elements. Neural networks are adjusted, in order to lead a specific target output, for particular input. Based on an estimation of the output and the target, the network is adjusted, until the output matches the target. Neural networks can also be trained to solve problems that are difficult for conventional computers or human beings. In this paper, out of many network functions, pattern recognition network has been used. Pattern recognition networks 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 zeros with the exception of a 1 in element j, where j is the class they are to represent [4]. The benefit of ANN is that it learns from the observed data.

5. Experimental Results

The ANN classifier has been used for different types of classification. Pattern recognition is used for creation of network and scaled conjugate gradient backpropagation is used as training function. In this paper, three experiments have been performed. All experiments have been repeated 10 times for number of neuron selection and for getting the maximum accuracy 3, 8 and 10 numbers of neurons have been chosen for first, second and third experiments respectively. First experiment is the classification of normal mammogram and calcification. Confusion matrix of this experiment is shown in Table I.

Second experiment is the classification of mass tissue and calcification. Confusion matrix of this experiment is shown in Table II. Third experiment is classification of normal, mass tissue and calcification. Confusion matrix of this classification is shown in Table III. The performance matrices such as accuracy, sensitivity and specificity had been calculated using (5), (6) and (7) respectively, where TP is True Positive (denotes presence of disease), TN is True Negative (denotes absence of disease), FP is False Positive (denotes presence of disease, but in reality disease is not present), FN is False Negative (denotes absence of disease, but in reality disease is present). An accuracy of 95.5% for first classification, 93.2% for second classification, and 82.4% for third classification has been obtained. Performance analysis of all the classifications is shown in Table IV. Figure 3, 4, and 5 show Receiver Operating Characteristics (ROCs) of these experiments. ROC curves are drawn between true positive rate and false positive rate. A graph towards top left corner shows the good accuracy.

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

$$Sensitivity = \frac{TP}{TP + FN} \quad (6)$$

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

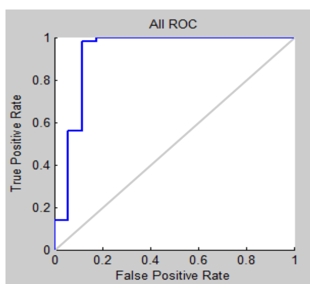

Figure 3. Neural Network Receiver Operating Characteristics of First Experiment

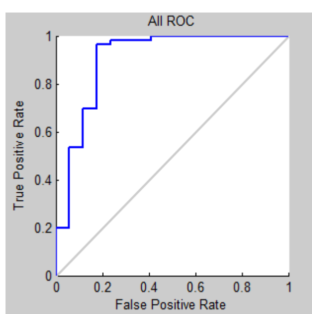

Figure 4. Neural Network Receiver Operating Characteristics of Second Experiment

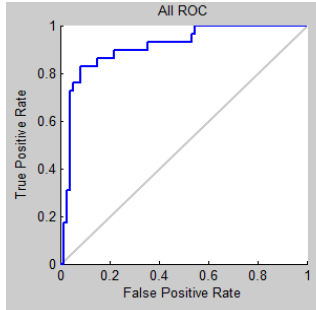

Figure 5. Neural Network Receiver Operating Characteristics of Third Experiment

Table I. Confusion Matrix of Normal Mammogram and Calcification

Actual Class	Predicted Class	
	Normal	Calcification
Normal	49	2
Calcification	1	15

Table II. Confusion Matrix of Mass Tissue and Calcification

Actual Class	Predicted Class	
	Mass	Calcification
Mass	55	4
Calcification	1	13

Table III. Confusion Matrix of Normal, Mass and Calcification

Actual Class	Predicted Class		
	Normal	Mass	Calcification
Normal	23	4	5
Mass	5	51	2
Calcification	1	1	10

Table IV. Performance Analysis of Proposed Method

Performance Metrics	Classification Analysis		
	Normal and calcification	Mass and calcification	Normal, mass and calcification
Accuracy	95.5%	93.2%	82.4%
Sensitivity	88.23%	76.47%	83.56%
Specificity	98%	98.21%	79.31%

6. Conclusion

The main purpose of this paper is to present a feature extraction technique, *i.e.*, BEMD for mammogram feature extraction. Features of mammogram images had been extracted using BEMD and mammograms were classified as normal, masses and calcification, using ANN pattern recognition method. An accuracy of 95.5% for first classification, 93.2% for second classification, and 82.4% for third classification was obtained. Results show that good accuracy has been obtained by using BEMD features with ANN. In future work classification of masses and microcalcification into benign and malignant classes can also be done to achieve the higher accuracy by using proposed method and this technique can be applied for other images also like cloud classification, CT and MRI images.

References

[1] http://www.breastcancer.org.
[2] http://www.cancer.org.
[3] http://peipa.essex.ac.uk/info/mias.html.
[4] www.mathworks.com.
[5] http://www.mathworks.in/matlabcentral.
[6] L. M. Bruce and N. Shanmugam, "Using Neural Networks with Wavelet Transforms for an Automated Mammographic Mass Classifier", Proceedings of the 22nd Annual EMBS International Conference, Chicago IL, **(2000)**.
[7] B. Verma and J. Zakos, "A Computer-Aided Diagnosis System for Digital Mammograms Based on Fuzzy-Neural and Feature Extraction Techniques", IEEE transactions on information technology in biomedicine", vol. 5, no. 1, (2001) March.
[8] J. E. Ball, T. W. Butler and L. M. Bruce, "Towards Automated Segmentation and Classification of Masses in Digital Mammograms", Proceedings of the 26th Annual International Conference of the IEEE EMBS San Francisco, CA, USA, **(2004)**.
[9] G. Zhang, H. Zhao, X. Zhang and P. Yan "A Computer Aided Diagnosis System in Mammography Using Artificial Neural Networks", International Conference on Biomedical Engineering and Informatics, **(2008)**.
[10] G. Vani, R. Savitha and N. Sundararajan, "Classification of Abnormalities in Digitized Mammograms using Extreme Learning Machine", 11th International Conference on Control, Automation, Robotics and Vision Singapore, **(2010)**.
[11] V. D. Nguyen, T. Van Nguyen, T. D. Nguyen, D. T. Nguyen and H. V. Hoang, "Detect Abnormalities in Mammograms by Local Contrast Thresholding and Rule-based Classification", 978-1-4244-7057-IEEE, **(2010)**.
[12] J. C. Nunes, 0. Niang, Y. Bouaoune, E. Delechelle and P. Bunel, "Texture analysis based on the Bidimensional Empirical Mode Decomposition with Gray- Level CO-occurrence models", IEEE. 0-7803-7946-, **(2003)**.
[13] G. Rilling, P. Flandrin and P. Gon¸Calv`Es, "ON EMPIRICAL Mode Decomposition and Its Algorithms", Conference on Nonlinear Signal and Image Processing, **(2003)**.
[14] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. -C. Yen, C. C. Tung and H. H. Liu, "The Empirical Mode Decomposition and The Hilbert Spectrum for Non-Linear and Non-Stationary Time Series Analysis", in Proc. R. Soc., Lond. A, vol. 454, **(1998)**, pp. 903-995.
[15] M. Vasantha, V. S. Bharathi and R. Dhamodharan, "Medical Image Feature, Extraction, Selection and Classification", International Journal of Engineering Science and Technology, vol. 2, no. 6, **(2010)**, pp. 2071-2076.
[16] D. M. Garge and V. N. Bapat, "A low cost wavelet based mammogram image processing for early detection of breast cancer", Indian Journal of Science and Technology, vol. 2, no. 9, ISSN: 0974- 6846, **(2009)**.
[17] A. AbuBaker, "Mass lesion detection using wavelet decomposition transform and support vector machine", International Journal of Computer Science & Information Technology (IJCSIT), vol. 4, no. 2, **(2012)**.
[18] J. Anitha and J. D. Peter, "A Wavelet Based Morphological Mass Detection and Classification in Mammograms", Machine Vision and Image Processing (MVIP), International Conference, ISBN 978-1-4673—2319-2, **(2012)**, pp. 25-28.
[19] Herwanto and A. M. Arymurthy, "Association Technique based on Classification for Classifying Microcalcification and Mass in Mammogram", IJCSI International Journal of Computer Science Issues, vol. 10, Issue 1, no. 2, **(2013)**.

[20] J. C. Nunes, Y. Bouaoune, E. Delechelle, O. Niang and P. Bunel, "Image analysis by bidimensional empirical mode decomposition", Image and Vision Computing, vol. 21, **(2003)**, pp. 1019–1026.
[21] S. Sondele and I. Saini, "Digital Mammograms Classification Using Artificial Neural Network Based On Bidimensional Empirical Mode Decomposition Features", International Journal of Electrical and Electronic Engineering & Telecommunications (IJEETC), ISSN 2319-2518, vol. 2, no. 3, **(2013)** July.

Authors

Srishti Sondele, she received her B.Tech degree in Electronics & Communication Engineering from CET IILM AHL, Uttar Pradesh Technical University, India in 2010. Presently, she is pursuing her M.Tech in Electronics & Communication Engineering from National Institute of Technology, Jalandhar, India.

Indu Saini, she received her B.Tech degree in Electronics & Communication Engineering from Guru Nanak Dev University, India in 1994 and then obtained her M.Tech (by Research) degree in Electronics & Communication Engineering from National Institute of Technology Jalandhar. Presently, she is pursuing her Ph.D. in the area of Biomedical Signal Processing from Dr B R Ambedkar National Institute of Technology Jalandhar, where she is also serving as Assistant Professor in Electronics & Communication Engineering Department since 2002.

