BREAST CANCER DETECTION ON THERMOGRAM AT PRELIMINARY STAGE BY USING FUZZY INFERENCES SYSTEM

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ABSTRACT

Thermogram is considered as one of the most effective methods for early detection of breast cancers. However, it is difficult for radiologists to detect Microcalcification clusters. Therefore, a computerized scheme for detecting early-stage Microcalcification clusters in mammograms is proposed. Optimal set of features are selected by Genetic algorithm which are fed as input to Adaptive Neuro fuzzy inference system for classifying image into normal, suspect and abnormal categories. This method has been evaluated on 322 images comprising normal and abnormal images. The performance of the proposed technique is analyzed in terms of convergence time. The results show that the features used are clinically significant for the accurate detection of breast tumor.

Keywords: Breast Cancer, Image classification, Genetic algorithms, Adaptive Neuro Fuzzy Inference System.

1. INTRODUCTION

Breast cancer is the primary cause of death in women over 40 years old in the world [1]. Its early detection can significantly increase the percentage of survival of the patients. Breast cancer is visible in the channel that transfers milk to the nipple and in the lobules of glands which generates milk. Cancer is a disease fixed in a social, cultural and economic structure as well as social behaviour, political agendas, individual behaviour and function of cells and their items. [14-15].

During the year 2003–2007, 68 years were the average fatal age for the breast cancer. The approximate percentages of deaths due to breast cancer according to age group are as follows: under 20(0.0%), 20-34 (0.9%), 35-44 (6.0%), 45-54 (15.0%), 55-64 (20.8%), 65-74 (19.7%), and 75-84 (22.6%) and above 85 (15.1%) years. It has been reported that diagnosis according to age group was 0% for under 20years of age, 1.9% (20-34), 10.2% (35-44), 22.6 % (45-54), 24.4% (55-64), 19.7% (65-74), 15.5 % (75-84), and 5.6% for those having the age above 85years [16].

It can be detected by analysing the Microcalcification, i.e., small objects are located on the breast tissue. These can be viewed by a radiologist on digital mammograms. Depending on the size and type of these elements; it is possible for a radiologist to diagnose whether a tumor is malignant or not without the need of a surgical procedure. One Microcalcification feature that can be used to distinguish the type of tumor whether it has smooth or rugged borders. Defining the nature of Microcalcification borders can help radiologists to classify these elements into several types [3]. This would help radiologists to further classify the tumor being analysed. Microcalcifications are high-frequency components on digital images. A transform that deals with frequency components can be used in trying to detect these objects on the breast image. The wavelet transform is used on the proposed work to detect these elements and to classify the nature of their borders, being smooth or rugged.

The wavelet transform is a mathematical tool which is used to analyse and process information regarding frequency components on an input signal. It uses two analysing functions: the scaling function and the wavelet function. These functions are applied through the signal by stretching and translation operations [7]. If the input signal is an image, the result of this operation is composed of two images: first one is composed of low frequencies of the input image, the second one is composed of other three containing high frequencies of the original image one with horizontal, one with vertical, and the last one with...
diagonal details. Since Microcalcification is located in digital mammograms composed of high-frequency components, the wavelet transform is used to detect and classify them.

Several researchers have introduced different approaches for classifying the mammogram images. A histogram intersection based image classification was proposed in [4]. Initially they had used the bag-of-words model for image classification in capturing the texture information. A normalized histogram intersection with the K-nearest neighbourhood classifier was applied. The classification accuracy depends on the normalization of the histogram.

The mammogram image classification is based on rough set theory in conjunction with statistical feature extraction techniques. The features which were derived from the gray level co-occurrence matrix were normalized and the rough set dependency rules generated from the attribute vector. The generated rules were passed to the classifier for the classification purpose [11].

In [12], it presents a new approach for the parenchymal pattern classification in which texture models were used to capture the thermogram appearance within the area of the breast. Parenchymal density patterns are modelled as the statistical distribution of clustered, invariant filter responses in low dimensional space. Fractal can be used to classify and distinguish various types of cells. The shapes of fractal objects kept invariant upon successive magnifying or shrinking the objects. Hence, fractal geometry can be applied to overcome the scale problem of texture. Fractal dimension can be defined in connection with real world data and can be measured. The curve, surface and volumes are complex objects for which ordinary measurements become limited because of their physical properties. Different techniques have been proposed to measure the degree of complexity by evaluating how fast the length, surface or volume increases with respect to smaller and smaller scales [12].

Thermography is a non-persistent, cost-effective and quick diagnostic method that treats the patient not by touching them and also it does not cause any pain [17 - 19].

In [20] it has shown that Complementary Learning Fuzzy Neural Network (CLFNN) complements breast thermography in various ways. The combination of breast thermography and CLFNN give rise to more consistent result than merely using breast thermography. Whether it is cancer detection or tumor classification, LFNN outperforms conventional methods which shows the strength of complementary learning in the recognition task. FALCON-AART assists physicians in distinct diagnostic tasks by providing a relatively accurate decision support tool, which could potentially enhance patient’s outcome. FALCON-AART not only gives superior results compared with conventional methods, but also offers an intuitive positive and negative fuzzy rule to explain its reasoning process.

Thermal cameras for imaging of the patients were used. Important parameters were derived from the images for their posterior analysis with the aid of a genetic algorithm. The principal components that were entered in a fuzzy neural network for clustering breast cancer were identified [21].

A new approach to classify mammogram images based on fractal features for a given mammogram image, first it eliminates all the artefacts and then it extracts the salient features such as Fractal Dimension (FD) and Fractal Signature (FS). These features provide good descriptive values of the region. Second, a trainable multilayer feed forward neural network has been designed for the classification purposes and the test results are compared with K-Means [2].

Breast cancer is one of the leading type of cancer diagnosed in women. For years human limitations in interpreting the thermograms possessed a considerable challenge, but with the introduction of computer assisted detection/diagnosis (CAD), this problem has been addressed. The problem compares different approaches based on neural networks and fuzzy systems which have been implemented in different CAD designs. The greatest improvement in CAD systems was achieved with a combination of fuzzy logic and artificial neural networks in the form of FALCON-AART complementary learning fuzzy neural network (CLFNN). With a CAD design based on FALCON-AART, it was possible to achieve an overall accuracy of nearly 90% [8].

Early detection of breast cancer is the key to improve survival rate. Thermogram is a promising front-line screening tool as it is able to warn women of breast cancer up to 10 years in advance. However, analysis and interpretation of thermogram are heavily dependent on the analysts, which may be inconsistent and error-prone. In order to boost the accuracy of preliminary screening, thermogram is used without incurring additional financial burden. Complementary Learning Fuzzy Neural Network (CLFNN) is proposed as the Computer-Assisted Intervention (CAI) tool for thermogram analysis. The CLFNN is a neuroscience-inspired technique that provides
intuitive fuzzy rules, human-like reasoning, and good classification performance. Confluence of thermogram and CLFNN offer a promising tool for fighting breast cancer [9].

In [13], it proposed a method for discrimination and classification of mammograms with benign, malignant and normal tissues using independent component analysis and neural networks. Those methods was tested for a mammogram set from MIAS database, and multilayer perceptron neural networks, probabilistic neural networks and radial basis function neural networks.

Thermal imaging is a non-invasive imaging procedure used to record the thermal patterns using Infrared (IR) camera. The aim of this study is to evaluate the feasibility of using thermal imaging as a potential tool for detecting breast cancer. They have used 50 IR breast images (25 normal and 25 cancerous) collected from Singapore General Hospital, Singapore. Texture features were extracted from co-occurrence matrix and run length matrix. Subsequently, these features were fed to the Support Vector Machine (SVM) classifier for automatic classification of normal and malignant breast conditions. [10]

In [18], computer routines were used to perform ROI identification and image segmentation of infrared images recorded from 19 patients. Asymmetry analysis between contralateral breasts were carried out to generate statistics that could be used as input parameters to a back propagation ANN. A simple 1-1-1 network was trained and employed to predict clinical outcomes based on the difference statistics of mean temperature and standard deviation. Results comparing the ANN output with actual clinical diagnosis were presented. Future work will focus on including more patients and more input parameters in the analysis. Performance of ANN network can be studied to select a set of parameters that would best predict the presence of breast cancer.

3D finite element method (FEM)-based thermal and elastic modelling techniques are developed to characterize comprehensively both the thermal and elastic properties of normal and tumorous breast tissues during static and dynamic thermography. Specifically, the tumor-induced thermal contrast shows an opposite initial change and delayed peak as compared with the deformation-induced thermal contrast. These findings are expected to provide a stronger foundation, greater specificity and precision for thermographic diagnosis, and treatment of breast cancer [6].

A thermal camera for imaging of the patients is used [5]. By using genetic algorithm the significant parameters were derived from the images for their posterior analysis. For clustering the breast cancer the prime components that were entered in a fuzzy neural network were also identified.

The rest of the paper is organized as follows. In the next section we have illustrated the proposed work of Fuzzy Inference system. In Section 3, we review the main properties of Cubic Interpolation. In Section 4, the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm is practiced to enhance the low contrast images. In Section 5, Discrete Wavelet Haar transforms and feature extraction is presented for enhancing the image at three different levels. In Section 6, the feature selection and fuzzy inference systems shows that extracted results will be exposed to a genetic algorithm and neural network stage for data optimization. Finally the set of images are obtained and then the experimental results are presented.

2. PROPOSED WORK

It has proposed a methodology for the classification of breast cancer by using the several approaches.

In this letter, time complexity has been achieved with the assistance of Neuro-Fuzzy systems than computing manually. The process is conceded initially with the thermogram image. It is practised since the image obtained by this method is clearer and can be viewed in different shades when compared to mammographic image as it uses just two colours black and white.

The aim of this paper is to establish the clear idea regarding the approaches in image processing. The input image is the thermogram image and then proceeded with the interpolation. Contrast Limited Adaptive Histogram Equalization (CLAHE) is used for enhancement of low-contrast medical images.

Mammography has been the most efficient tool for screening of microcalcification and cancer tissues. However, the raw images produced by mammography systems are usually of poor contrast. In order to use these raw images for early diagnosis, their contrast, sharpness and noise are needed to be enhanced. Among these important enhancement parameters contrast enhancement is critical. A novel algorithm is introduced which blends wavelet transforms with Contrast Limited Adaptive Histogram Equalization for contrast enhancement. In this algorithm, the input image is decomposed to its low frequency and high frequency components in wavelet domain. Decomposed coefficients from different bands are
then manipulated. Manipulation of decomposed images consists of applying the modified CLAHE algorithm. The new algorithm was tested on a number of mammogram images. To gauge the potential of the new algorithm, the results were compared with results of CLAHE algorithm.

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3. CUBIC IMAGE INTERPOLATION

Four grid points are needed to evaluate the interpolation function and two grid points on either side of the point for one-dimension Cubic Convolution Interpolation. 16 grid points are needed to evaluate the interpolation function for Bicubic Interpolation (cubic convolution interpolation in two dimensions), two grid points on either side of the point for both horizontal and vertical directions. The grid points needed for one-dimension and two-dimension cubic convolution interpolation are shown in Figure 1.

The technique of Bicubic interpolation produces less blurring of edges and other distortion artifacts than bilinear interpolation, but is more computationally demanding. Bicubic interpolation involves fitting a series of cubic polynomials to the brightness values contained in a $4 \times 4$ array of pixels surrounding the calculated address.

The cubic convolution interpolation kernel is composed of piecewise cubic polynomials defined on the subintervals $(-2, -1), (-1, 0), (0, 1)$, and $(1, 2)$. Outside the interval $(-2, 2)$, the interpolation kernel is zero. As a consequence of this condition, the number of data samples used to evaluate the interpolation function is reduced to four. The system flow of knowledge based inference system is shown in Figure 2 the interpolation kernel must
be symmetric. Coupled with the previous condition, this means \( K_i \) that must have the form

\[
K_i(t) = \begin{cases} 
(1+2|t|)^3 - (1+2|t|) & \text{if } |-1| < t < 1 \\
0 & \text{otherwise}
\end{cases}
\]  

(1)

Where \( \alpha \) is a free parameter. This function is derived by finding a piecewise cubic polynomial with knots at the integers that is required to be symmetric, \( C_1 \) continuous, and have support in \(-2 < t < 2\). These conditions leave one remaining degree of freedom represented by \( \alpha \). For any value of \( \alpha \), \( K_1 \) has external points at \( t = 0 \) and \( \pm \frac{4}{3} \). Additional knowledge about the shape of the desired result may be imposed upon equation (1) which yield bounds on the value of \( \alpha \). The heuristics applied to derive the kernel are motivated from properties of the ideal reconstruction filter, the sinc function.

4. CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION

Each time an image is acquired, window and level parameters are adjusted to maximize contrast and structure visibility. This must be done before the image is saved in any other format than the generic format of the acquisition software. For a moment, very little post-processing in addition to window-level is applied to the image after its acquisition. This is a part to be the good quality of the image without processing, but also because of the short experience and tools 16bit images are used. Contrast Limited Adaptive Histogram Equalization (CLAHE) seems to be a good algorithm to obtain a good looking image directly from a raw Hospital Information System (HIS) image, without window and level adjustment. This is one of the possibilities to automatically display an image without user intervention. Further investigation of this approach is necessary. The CLAHE was originally developed for medical imaging and has proven to be successful for enhancement of low-contrast images such as portal films.

The CLAHE algorithm partitions the images into contextual regions and applies the histogram equalization to each one. This even out the distribution of the used grey values and thus makes hidden features of the image more visible. The full grey spectrum is used to express the image. CLAHE is an improved version of Adaptive Histogram Equalization (AHE). Both overcome the limitations of standard histogram equalization.

Figure 3: Histograms Of Input Thermographic Image

Figure 4: Histograms Of Enhanced Thermographic Image

A variety of adaptive contrast-limited histogram equalization techniques are provided. Sharp field edges can be maintained by selective enhancement within the field boundaries. Selective enhancement is accomplished by first detecting the field edge in a portal image and then processing those regions of the image that lie inside the field edge. Noise can be reduced while maintaining the high spatial frequency content of the image by applying a combination of CLAHE, median filtration and edge sharpening. This technique is known as Sequential processing, and can be recorded into a user macro for repeated application at any time.

A variation of the contrast limited technique called Adaptive Histogram Clip (AHC) can also be applied. AHC automatically adjusts the clipping level and a moderate over enhancement of
background regions of portal images. AHE has a tendency to over amplify the noise in relatively homogeneous regions of an image. The application of Contrast Limited Adaptive Histogram Equalization in the figure 3 and figure 4 is found to be one of the most suitable alternatives since it fulfills all the desired objectives such as Image clarity (i.e., the clarity to its fullest intensity), Equalizing the contrast projection, and preventing over-amplification of noise signals by imposing limiting characteristic. The Figure.3 and Figure.4 shows the histograms of input and enhanced thermographic image.

5. DISCRETE HAAR WAVELET TRANSFORMATION AND FEATURE EXTRACTION

An outstanding property of the Haar functions is that except function Haar (0, t), the i-th Har function can be generated by the restriction of the (j − 1)-th function to be half of the interval where it is different from zero, by multiplication with 2^j and scaling over the interval [0, 1]. These properties give considerable interest of the Haar function, since they closely relate them to the wavelet theory. In this setting, the first two Haar functions are called the global functions, while the others are denoted as the local functions. Hence, the Haar function, which is an odd rectangular pulse pair, is the simplest and oldest wavelet.

The motivation for using the discrete wavelet transform is to obtain information that is more discriminating by providing a different solution at different parts of the time–frequency plane. The wavelet transforms allow the partitioning of the time-frequency domain into non-uniform tiles in connection with the time–spectral contents of the signal. The wavelet methods are strongly connected with classical basis of the Haar functions; scaling and dilation of a basic wavelet can generate the basis Haar functions. Let ψ → R, R the Haar wavelet function is defined by the formula

\[
\psi(t) = \begin{cases} 
1, & \text{for } t \in \left[0, \frac{1}{2}\right], \\ 
-1, & \text{for } t \in \left[\frac{1}{2}, 1\right), \\ 
0, & \text{otherwise} 
\end{cases}
\]

The aim of the feature extraction step is to feed the classifier with relevant features that must be chosen to maximize interclass variance. For instance the mammogram images can be described by frequency analysis using discrete haar wavelet transform.

In feature extraction, the textural features and Gabor features are extracted by using discrete wavelet transform and the GLCM. The histogram technique is mainly used to extract the features. Initially, the input thermographic image is shown in the above Figure.5 which undergoes the process to extract the features. First step is to convert the input image into the gray scale thermographic image as shown in the Figure.6 in order to obtain the exact scaling. The next step is to enhance the gray level image in two different levels namely first level and second level of enhancing the image as shown in the Figure.7 and Figure.8. After enhancing the image in the gray level, the image is then enhanced in at three different levels. This undergoes first level, second level and third level of enhancement which is shown in the Figure.9, Figure.10 and Figure.11.
6. FEATURE SELECTION AND ADAPTIVE NEURO FUZZY INFERENCE SYSTEMS

Initially, patients underwent thermal imaging, after which the images were processed. The extracted results were subjected to a genetic algorithm and neural network stage for data optimization. The GA searches for global solutions and does not require the objective function to be differentiable. The extracted properties of thermal images were: 1) Autocorrelation, 2) Correlation, 3) Homogeneity, 4) Maximum Probability, 5) Difference variance, 6) Inverse Difference Moment Normalized (IDMN) of the sample 13 mammogram images from the MIAS database. The process flow of neural structure is shown in the Figure 12.
Samples of the images obtained are shown in Figure 5. The first step of this method is the diagnosis of the breast. The component of image intensity directly depends on thermal energy delivery to the correlated areas. A histogram expresses the delivery intensity. It explains image combination. The moments of the histogram gives statistical information about the texture of the image. The Figure.13 shows the adaptive neuro fuzzy inference system rule. The Figure.14 shows the histograms of enhanced thermographic image based on time complexity.

An effective and simple method for the purpose of selecting significant input variables and
determining optimal number of fuzzy rules when building a fuzzy model from data is proposed. By comparing with the existing clustering-based methods, these methodologies both input selecting and partition validating are determined on the basis of a class of sub-clusters created by a self-organizing network instead of a data.

![Graph showing system validation in Adaptive Neuro Fuzzy Inference after training using hybrid technique](image)

**Figure 15:** System Validation in Adaptive Neuro Fuzzy Inference after Training Using Hybrid Technique

The important input variables which independently and significantly influence the system output can be extracted by a fuzzy neural network. On the other hand, the optimal number of fuzzy rules can be determined separately via the fuzzy c-means algorithm with modified fuzzy entropy as the criterion of cluster validation. The simulation results displays that the proposed method can provide good model structures for fuzzy modeling with high computing efficiency.

The Figure 15 consists of 13 images in X-axis and 2 outputs (normal and abnormal) in Y-axis. The coincidence of the two symbols, training data and fuzzy inference system shows that the exact classification of data. The average error in the training and testing of the proposed neuro fuzzy system are 0.000102828 and 0.00025222 for 2 epochs.

Adaptive Neuro Fuzzy Inference Systems (ANFIS) combines the learning capabilities of neural networks with the approximate reasoning of fuzzy inference algorithms. ANFIS uses a hybrid learning algorithm to identify the membership function parameters of Sugeno type fuzzy inference systems. The aim is to develop ANFIS-based learning models to classify normal and abnormal images from mammogram image to detect breast cancer. An adaptive neural network is a network structure consisting of five layers and a number of nodes connected through directional links. The first layer executes a fuzzification process, second layer executes the fuzzy AND of the antecedent part of the fuzzy rules, the third layer normalizes the fuzzy membership functions, the fourth layer executes the consequent part of the fuzzy rules and finally the last layer computes the output of the fuzzy system by summing up the outputs of the fourth layer [6].

Each node is characterized by a node function with fixed or adjustable parameters. Learning or training phase of a neural network is a process to determine the parameter values to sufficiently fit the training data. Based on this observation, a hybrid-learning rule is employed here, which combines the gradient descent and the least-squares method to find a feasible set of antecedent and consequent parameters. In order to obtain the set of rules and to avoid the problems inherent in grid partitioning based clustering techniques, subtractive clustering is applied. This technique is employed since it allows to scatter input-output space partitioning. The subtractive clustering is one pass algorithm for estimating the number of clusters and the cluster centres through the training data.

Autocorrelation, also known as serial correlation, is the cross-correlation of a signal with itself. Informally, it is the similarity between observations as a function of time lag between them. Correlation refers to any of the broad class of statistical relationship involving dependence. Generally homogeneity is defined as the quality or state of being homogeneous. It is also means having a uniform structure throughout. For instance, a uniform electric field would be compatible with homogeneity.

Probability is a measure of the likeliness that an event will occur. It is used to quantify an attitude of mind towards some proposition of whose truth we are not certain. Variance measures how far a set of numbers is spread out. A variance of zero indicates that all the values are identical. Variance is always non-negative: a small variance indicates that the data tend to be very close to mean.

Neural network are computation models inspired by an animal’s central nervous system which is capable of machine learning as well as pattern recognition. Artificial neural network are generally presented as system of interconnected neurons which can compute values from inputs.
8. CONCLUSION

This paper presented a new application of ANFIS for the classification of breast cancer. The presented ANFIS model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach. The choice of suitable feature space is often problem dependent and features in Table 1 are therefore usually adapted to the image content. From thermal images the extracted properties are Autocorrelation, Correlation, Homogeneity, Maximum Probability, Difference Variance, Inverse Difference Moment Normalized (IDMN). The results are more accurate if the process takes place in the same order. The classification results and statistical measures were used for evaluating the ANFIS while evaluating the system with the sample of images, the average time complexity seems to be below 0.5 second. It is concluded that the proposed ANFIS model can be used in classifying the breast cancer by taking into consideration the classification rates. In future, it will consider other statistical models for K-Means in order to improve the classification rate.

REFERENCES


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