

# Analysis of Breast Thermography with an Artificial Neural Network

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**Abstract**— Thermal imaging has been used for early breast cancer detection and risk prediction since the sixties. Examining thermograms for abnormal hyperthermia and hyper-vascularity patterns related to tumor growth is done by comparing images of contralateral breasts. Analysis can be tedious and challenging if the differences are subtle. The advanced computer technology available today can be utilized to automate the analysis and assist in decision-making. In our study, computer routines were used to perform ROI identification and image segmentation of infrared images recorded from 19 patients. Asymmetry analysis between contralateral breasts was carried out to generate statistics that could be used as input parameters to a backpropagation 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 are 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.

**Keywords**—Breast cancer detection, risk prediction, thermography, thermal, infrared imaging, artificial neural network, ANN

## I. INTRODUCTION

Breast cancer has been known for decades to be the most common type of cancer among women. Despite the high incidence rate, the breast cancer mortality rate has actually been decreasing since the late eighties. Most medical experts and researchers credit the encouraging results to early breast cancer detection as well as better cancer treatment. However, mammography, the most widely employed detection method, is not as effective for women with dense or surgically altered breasts, or women aged 40 and younger. Furthermore, there is concern regarding the risk of ionizing radiation and patients' complaints of discomfort due to the high compression of the breasts. In searching for other imaging techniques to complement mammography, thermography has re-emerged as a potential method to improve overall detection efficiency.

Application of thermography or infrared imaging for early breast cancer detection and risk prediction has been widely studied since the sixties. Researchers have demonstrated that breast thermography has great potential for early cancer detection and prognosis indication, used either independently or in conjunction with mammography [1-3]. Medical thermography is a method of quantifying body surface temperature by measuring infrared radiation emitted by human skin. As metabolic heat is carried

throughout the body mainly by convection through blood flow, an increase in localized skin temperature usually indicates an increase in blood flow around the "hot" spot. Hyperthermia around the tumor is thought to be caused by one of two mechanisms: 1) higher metabolic rate of the cancerous cells and 2) angiogenesis of the tumor. Angiogenesis (formation of new blood vessels) of the tumor has been widely investigated and found to be a significant prognosis indicator for breast cancer [4-5]. Microvessel density (MVD) is used to measure the extent of the angiogenesis. A lower MVD has been shown to correspond to higher disease free survival [6]. Infrared cameras can capture an increase in blood vessel density that leads to neovascularization (vascular hot spots).

Despite showing great potential, breast thermography which is non-invasive, painless, and relatively inexpensive is still experiencing skepticism among healthcare professionals. Over the last few decades, clinical trials have demonstrated varying results [7-8]. The inconsistencies are partly due to image acquisition equipment and procedures, complicated processing and analysis of the thermograms and most importantly, lack of standard protocols to guide the final prediction. Evaluation of the thermograms was often done manually and thus affected by human subjectivity. With the advanced computer technology and image processing tools available today, analysis of the images could be done faster and more thoroughly by specially designed computer programs. Artificial neural networks (ANN), which model the structure of the human brain, have been used successfully for pattern recognition problems. Once the ANN is properly trained, it can be used to generate consistent output for new sets of inputs reliably and objectively. ANN is widely recognized as a valuable clinical decision support tool.

## II. METHODOLOGY

### A. Image Acquisition

This study analyzed thermal images of 19 patients with known clinical outcome taken from a database of 86 patients at Moncton Hospital's breast cancer screening clinic. The thermal images were recorded in 1984 by Dr. Monique Frize and her team, using a first generation thermographic camera Thermovision 680 Medical from Agatronics connected to an OSCAR 780 (Off-line System for Computer Access & Recording (Agatronics)). Data collection in Moncton followed a rigid protocol to ensure best results. The tests

were performed in the week following menstruation or between the 6<sup>th</sup> and 10<sup>th</sup> day of the cycle, up to the 13<sup>th</sup> day.

For data collection, the patient was asked to avoid alcohol, caffeine, pain medication lotions, and stop smoking two hours before the test. The chest area was cooled slightly with a fan for approximately 10 minutes just prior to the image taking. The room temperature was approximately 22 degrees Celsius and darkened during the test. The images were taken and stored on a digital tape recorder for later playback and analysis. This approach provided the best temperature contrast between hot and cold areas on the body. The matrix for each image consisted of 128 X 128 pixels. The gray scale values ranged from 0 to 255 and were mapped to temperature values using the mean temperature value obtained from the camera as a reference.

### B. Image Processing

A semi-automated segmentation of the breasts was used in this study. The first step was to identify the outside boundaries of each breast. An automated technique was investigated that assumed an elliptic shape for the breast boundaries. The image contrast was first enhanced by using a disk of 5-pixel radius to perform top-hat and bottom-hat morphological filtering operations, thereby emphasizing the contours and the edges in the images. Edges were then detected using a Canny edge detector. The outermost body edges were neglected in the edge detection step. Detected edges were further trimmed of all edge contours corresponding to vertical or horizontal lines since they were likely artifacts from the edge detection or from the image itself and did not relate to intuitive breast features.

It was hypothesized that the center of mass of all the edges was likely located within the breast area; thus, edges closer to this center of mass were considered more likely to belong to the breast area. An inclusion factor was derived that determined the cutoff distance from the center of mass. Finally, the smallest convex region enclosing the remaining edges was sought and the ellipse that best fitted its contour was chosen as the most likely breast area. The ellipse-fitting algorithm was obtained from Halir and Flusser's paper [9]. The same procedure was repeated for both sides. Although the automated segmentation of the outer boundaries of the breasts performed well in most images, we were unable to achieve satisfactory segmented breasts in all images. As a

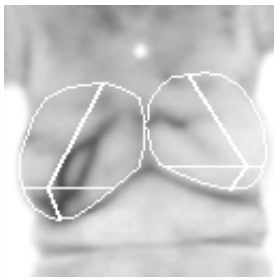


Fig. 1. Breast images with ROI identified and four quadrants shown.

result, the boundaries of the breasts were manually segmented to ensure consistency between all images.

The breasts were further divided in four quadrants, as shown in Fig. 1, according to a division suggested by Lipari and Head [10]. This process was automated using easily identified points in the image such as the nipple and the chin. The nipple was identified through a rule-based detection algorithm and assumed to be a circular-shaped area within the lower part of the breast. The algorithm is summarized as follows:

1. A Canny edge detector with adaptive thresholds is used to find the edges within the breast.
2. Morphological bridging operations are performed to obtain closed contour regions.
3. Bigger contour regions and regions in the upper breasts are discarded, as they are unlikely candidates for the nipple area.
4. The circular nature of each contour region is assessed by fitting an ellipse to the regions and evaluating the eccentricity of the best fitting ellipse. The region with an eccentricity closest to one is chosen to be the nipple.

The chin was assumed to be on the vertical symmetry line between contralateral sides and thus easily found. When the chin was not present, the uppermost pixel of the vertical symmetry line was used for the upper quadrants division.

Statistical parameters were computed for each breast and each quadrant within the breasts: mean, standard deviation, median, maximum, minimum, skewness, kurtosis, entropy, area and heat content. As a visual inspection of the breast images usually involves a symmetry analysis of the contralateral breasts, the difference statistics between contralateral breasts were used as input features to the neural network analysis.

### C. Image Analysis with ANN

A backpropagation (BP) neural network was used to analyze the infrared breast images described above. BP neural network, applied extensively in pattern recognition problems is a feedforward network with an input layer, an output layer and at least one hidden layer. For this analysis, the BP neural network was implemented with MATLAB Neural Network Toolbox built in functions. The Neural Network Toolbox supports most commonly used network architectures with flexibility for customization. The input vector to the neural network consisted of the breast image statistics. Due to the small data set available for analysis, network architecture was limited to 1 hidden layer with 1 to 4 nodes.

In determining the input data sets, a correlation analysis of the statistical parameters was performed using SPSS statistics software. Of the ten parameters extracted from each breast image, five were found to be highly correlated with one or more parameters, and therefore were considered redundant. The five parameters chosen for further analysis were mean, standard deviation, skewness, kurtosis and heat

content. Two backpropagation training algorithms were compared for suitability: the Levenberg-Marquardt (trainlm) and the Resilient Backpropagation (trainrp). The Levenberg-Marquardt (LM) algorithm was chosen as it generally yields the fastest convergence and the lowest mean square error (MSE), especially for relatively small networks. The Resilient Backpropagation (RP) algorithm has been described as the fastest algorithm for pattern recognition problems [11]. The transfer function used for all neurons was the tan-sigmoid function. All inputs were normalized to be in the range of -1 and 1.

Given the 19 images available for this analysis, the BP network was trained with 18 images and validated with the 19<sup>th</sup>. The experiment is summarized as follow:

1. Initialize the network to randomly generate an initial set of weights and biases for the neurons.
2. Select a test image to be used later for validating the ANN, and train the network with the remaining 18 images.
3. With the trained network from Step 2, validate the network with the test image to generate an output.
4. Compare the ANN output with the clinical diagnosis for that particular image.
5. Reiterate Step 1 to Step 4 19 times until all 19 images have been selected as a test image once

Reinitializing the weights and biases of the neurons ensured that the subsequent training session was independent of the previous session. Otherwise the network would appear to have been trained with 342 (19x18) images. For any given network configuration, step 1 to step 5 was typically executed 10 times, and the cumulative results from step 4 were inspected to assess the overall performance of the network configuration in differentiating abnormal thermograms from normal thermograms. Once that was established, the network configuration was modified. The modification generally followed these guidelines:

1. If the training does not meet the performance goal (MSE specified) or does not yield fast convergence (training results from step 2), the number of hidden nodes is increased.
2. If the training meets the performance goal but the output generated in step 4 is not consistent, the number of input parameters is decreased.
3. If the training meets the performance goal and the output generated in step 4 for the same image is consistent, the number of hidden nodes is decreased to obtain the smallest network achievable.

The goal of the analysis was to evaluate the suitability of the ANN to assist a physician during the process of breast thermogram examinations.

### III. RESULTS

With all five statistics (mean, standard deviation, skewness, kurtosis, and heat content) used as input

parameters, a small network configuration such as a 1-2-1 was not able to converge for more than half of the training sessions. The number of hidden nodes was therefore increased. Although a 1-4-1 network was able to meet the performance goal, the outputs generated from the simulation were highly inconsistent. The network might have been overfitted since the size of the training set was small for the number of the input parameters. The input parameters were therefore reduced. In this analysis, the network demonstrated the highest predictive power when the input parameters were decreased to two. With two input parameters, the network configuration was reduced to one hidden node. The two parameters selected were the difference statistics for mean temperature and standard deviation. Mean temperature difference was selected based on previous work on analysis of thermal images [2]. Standard deviation was included after a visual inspection of the breast images, as it indicated the spread of the pixel values across the infrared images. A large standard deviation value could indicate a highly vascular breast image.

Two sets of difference statistics were used in the analysis, one computed for the whole breast, and one for each quadrant of the breast. For the whole breast data, two input parameters for the ANN were 1) mean difference calculated between the contralateral breasts and 2) square of the standard deviation difference between the contralateral breasts. With the breast quadrant statistics, the two input parameters were computed based on the following formulas:

Input Param 1:

$$\text{Abs}(Q1\_mean\_diff + Q2\_mean\_diff + Q3\_mean\_diff + Q4\_mean\_diff)$$

Input Param 2:

$$\text{sqr}(Q1\_std\_diff) + \text{sqr}(Q2\_std\_diff) + \text{sqr}(Q3\_std\_diff) + \text{sqr}(Q4\_std\_diff)$$

The formula used to calculate the first input parameter was previously suggested by Head et al [12].

Both trainrp and trainlm algorithms were used with the 1-1-1 BP network for comparison. It was observed that the network trained with RP consistently met the performance goal set at  $10^{-8}$ . Furthermore, the ANN correctly predicted the outcome of 18 test images out of the 19 in the experiment. With the whole breast statistics, a false negative outcome was consistently given to patient #17 who had been diagnosed with cancer. With the breast quadrant statistics, a false negative outcome was consistently predicted for patient #7. Similar observations were obtained for ANN trained with LM algorithm and whole breast statistics. With the breast quadrant statistics, the ANN was able to make all correct predictions in more than half of the experiments. Table 1 shows an example of the results obtained from the ANN analysis.

TABLE I  
A SAMPLE ANN OUTPUT FOR BOTH SETS OF STATISTICS

Patient	Clinical Diagnosis	Whole Breast		Breast Quadrants	
		Typical ANN Output		Typical ANN Output	
		RP	LM	RP	LM
1	normal	-1	-1	-1	-1
2	normal	-1	-1	-1	-1
3	normal	-1	-1	-1	-1
4	normal	-1	-1	-1	-1
5	normal	-1	-1	-1	-1
6	fibrocystic	-1	-1	-1	-1
7	cancerous	1	1	-1	1
8	normal	-1	-1	-1	-1
9	normal	-1	-1	-1	-1
10	normal	-1	-1	-1	-1
11	normal	-1	-1	-1	-1
12	normal	-1	-1	-1	-1
13	normal	-1	-1	-1	-1
14	normal	-1	-1	-1	-1
15	cancerous	1	1	1	1
16	cancerous	1	1	1	1
17	cancerous	-1	-1	1	1
18	normal	-1	-1	-1	-1
19	normal	-1	-1	-1	-1

(Normal: -1, Abnormal: 1)

#### IV. CONCLUSION

Analysis of breast thermography is a labor-intensive task that generally requires careful inspection of small temperature differences and abnormal vascular patterns. A BP neural network trained for pattern recognition problems can be used to assist in clinical decisions. In our analysis, we have demonstrated that a BP neural network was able to generate fairly accurate output based on the statistical input parameters computed from breast thermography. A possible explanation for the two false negative outcomes observed in our analysis could be the small sample of patients with cancer. With the limited number of images available for analysis, we have restricted the network to a simple configuration with one hidden node, and two input parameters: mean temperature difference and standard deviation difference. In order to fully assess the ability of ANN to predict true outcomes based on statistical inputs, more patients will be recruited to participate in the study. An ethics protocol is under development and a physician has agreed to provide a number of patients to complete this work at the Ottawa Women's Health Centre. The next series of tests should provide sufficient data to increase the sensitivity of the method substantially.

Future work should focus on including more statistical parameters into the thermal imaging analysis. Besides

asymmetry analysis, examinations of the vascular patterns on the breast images should be performed in evaluating the health of the breasts. The potential of fractal dimension as a measure of vascularity may be explored. A score of fractal dimension can be included as an input parameter to the ANN. With a larger set of training and validating data, the result pattern obtained from analyzing thermal images with the BP neural network can be used to select a set of parameters that will best predict an abnormal thermogram. Since electronic data can be easily stored for future retrieval, a "smart" ANN can be developed into a clinical decision support tool to improve the overall sensitivity and specificity of thermography for early breast cancer detection and risk prediction.

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