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AUTOMATED BREAST CANCER DETECTION VIA THERMOGRAPHY

Hugo de Morais Dourado Neto, hugodouradoneto@gmail.com
Heinrich Heine University, HHU - Institute for Computer Science
Rita de Cássia Fernandes de Lima, ritaflima@yahoo.com.br
Universidade Federal de Pernambuco, UFPE – Department of Mechanical Engineering

Abstract. *In order to validate the use of thermography as a test for breast cancer, the first fully automated method of thermogram processing and analysis is proposed. In this work, 84 patients from the age of 40 were tested under standardized environmental conditions, including 20 patients with cancer, 22 with benign tumor, 14 with cyst and 28 without abnormalities. With the use of common classification methods, the best result was 89.29% of accuracy, with respective 75% sensitivity and 93.75% specificity. The results are comparable with those of the standard test of mammography, and they strongly suggest the feasibility of this specific use of thermography.*

Keywords: Thermography, Breast Cancer, Medical Image Analysis

1. INTRODUCTION

Breast cancer is the leading cause of death by cancer among women in Brazil, and the early diagnosis is determinant in patients´ healing chances. Combined with the clinical exam done by the physician, the most common screening method is mammography, an anatomical test that permits to visualize malignant tumors directly. However, in Brazil it is recommended to be only done every 2 years for women between 50-69 years old, and between the ages of 40 and 49 only in case of a suspicious annual clinical exam. The restricted application of mammography is partially due its use of ionizing radiation, itself a factor that increases the risk of cancer (Silva and Hortale, 2011).

Infrared thermography is a technique that can be used to detect modifications in the breast temperature distribution caused by the presence of a malignant tumor (Jones, 1998). Although not permitting to visualize tumors directly, it has the advantage of being a non-invasive method that does not involve touching, venous access or ionizing radiation (Borchartt *et al.*, 2012).

The purpose of this study is to identify breast cancer patients based on the analysis of their thermograms. A fully automated analysis method, which is independent of possibly inaccurate human interpretations of the infrared images, allows us to quantify the effectiveness of this use of thermography. In order to develop a fully automated method, it is necessary to propose a segmentation method for the Region of Interest (ROI), and to identify the extracted features that produce the best classification results.

2. METHODOLOGY

The thermograms used in this study were acquired between 2005 and 2013 at the Hospital das Clínicas of the Federal University of Pernambuco, Brazil, following the protocol described in Oliveira (2012). The camera used was the FLIR S45 with a resolution of 320x240 pixels and sensitivity of 0.08 °C. Subjects of this study were patients from the age of 40, the recommended starting age for screening tests. Out of a total of 84 patients, 20 were diagnosed with malignant tumor (cancer), 22 with benign tumor and 14 with cyst confirmed by biopsy, and 28 were diagnosed as normal (without abnormalities) confirmed by mammography and ultrasonography exams. The acquired images were adjusted according to measured environmental temperatures, relative humidity and distances. Because the measured relative humidity had some peaks in the older acquisitions, we only considered images taken with measured relative humidity equal or inferior to 80%, a value that can be identified in the histogram of all measurements (Figure 1) as the antimode between two modes.

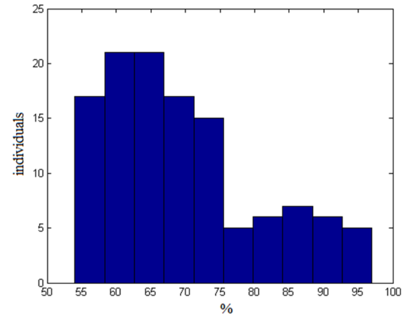

Figure 1. Histogram of all measured values of relative humidity.

2.1 Segmentation

The first step in analyzing breast thermograms is the identification of the ROI, for the following analysis not to be misguided by other information in the images. Some automated segmentation methods have been proposed. However, they are based on geometrical considerations that do not apply to all patients. This has caused an important loss of information in some cases (Marques, 2012) and the consistent inclusion of areas that are not part of the ROI (Motta, 2010). In the current study, we use a segmentation method that does not always result in an esthetically delicate definition of the ROI borders, but is expected to be useful for the purpose.

The segmentation of the temperature matrix began with the separation of the patient´s body region from the colder background. It was done by identifying the threshold value in the respective histogram that separates the two regions. Then the regions immediately beneath the armpits were identified and a straight line with an angle of 60° respective to the horizontal defined two superior regions that were excluded, together with the region above the neck. Finally, the region immediately under the breasts was identified and excluded according to its relatively higher local temperature.

2.2 Feature Extraction

Two features, temperature intervals that are described below, were extracted from the segmented temperature matrix. To test whether those values were significantly different between the samples of cancer and those without cancer, we analyzed the respective histograms and p-values. The p-values of the Kolmogorov-Smirnov test for normality were greater than 0.05 for each sample, so we considered each distribution as normal, and the t-test was used to compare the means.

2.2.1 Feature 1

First, we searched for the maximum temperature in each breast, but only in pixels with a value higher or equal to its immediate surroundings, and not in the border of the ROI. This criterion was used to avoid the influence of possible regions not properly excluded in the segmentation process. We then defined the difference between the maximum temperatures of each breast as the Feature 1.

2.2.2 Feature 2

Following a similar procedure, we searched for the minimum temperature of each breast, but only in pixels with temperature lower or equal to its immediate surroundings, and again not in the border of the ROI. We then defined the difference between the minimum of the two previously found maxima (one for each breast) and the maximum of the two minima as the Feature 2.

2.3 Classification

To find the best classification method for our purposes, we tested the five supervised learning methods present in the Statistics Toolbox™ of MATLAB® 2013b. They are: Classification Tree, Support Vector Machine, Discriminant Analysis, Naïve Bayes, and K-Nearest Neighbors. In each case, parameters were tested to achieve the best results. For the Classification Tree method, we used the standard parameters. For the Support Vector Machine method, we used a polynomial kernel of order 5. For the Discriminant Analysis method, we used the Mahalanobis distance. For the Naïve Bayes method, we used a kernel distribution. For K-Nearest Neighbors method, we also used the Mahalanobis distance. The chosen method to validate the results was the leave-one-out cross-validation.

In order to analyze the potential of the proposed method as a test for breast cancer, the accuracy, sensitivity and specificity were calculated, followed by the specificity in each class of benign, cyst and normal breast.

3. RESULTS

All the results, including figures, p-values, accuracies, sensitivities and specificities were acquired with the use of a main routine in MATLAB.

3.1 Segmentation

For all tested images, the performed segmentation was satisfactory, as none of them had important losses in the ROI or had included areas not from the ROI. Figure 2 is one example of the performed segmentation.

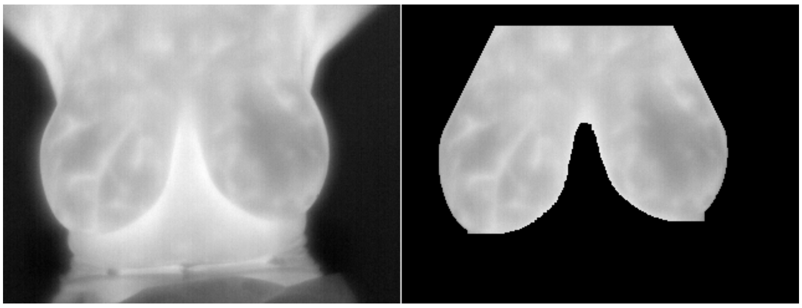

Figure 2: Original image represented in grayscale (left), result of the segmentation (right).

3.2 Feature Extraction

Feature 2 enables a good distinction between the samples of patients with cancer and patients without cancer, as illustrated in Fig. 3 and Tab. 1.

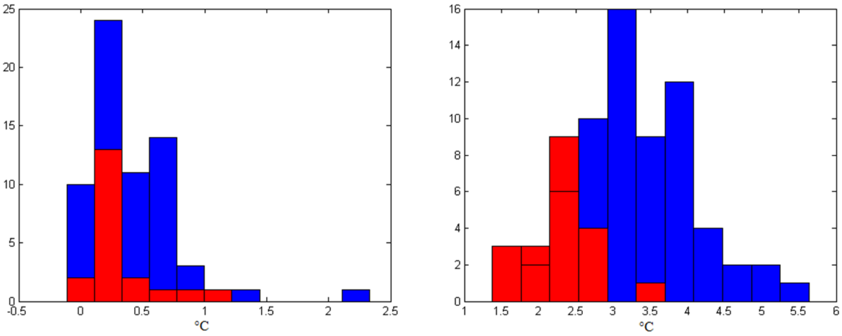

Figure 3: Histograms of Cancer (red) and not Cancer (blue) for the Feature 1 (left) and Feature 2 (right).

The histograms suggest that Feature 1 alone does not distinguish the two classes, and Feature 2 alone does distinguish them.

Table 1. p-values of the Kolmogorov-Smirnov test for normality and the p-values of the t-test.

Feature	Cancer	Not Cancer	t-test
Feature 1	0.066366585	0.179530089	0.224734678
Feature 2	0.824479517	0.896601539	0.000000001

We can conclude that the mean of Feature 2 is different between the two classes ($p < 10^{-8}$). Figure 4 suggests that the classes can be distinguished even better when the features are combined.

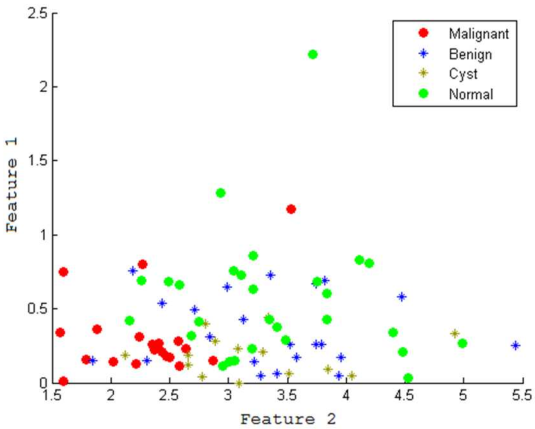

Figure 4: Scatterplot of the features for the four classes: malignant, benign, cyst and normal.

3.3 Classification

Table 2 presents the classification performance obtained using different classifiers, with leave-one-out cross-validation.

Table 2. Classification performance of different classifiers

Classifier	Accuracy	Sensitivity	Specificity (All)	Specificity Benign	Specificity Cyst	Specificity Normal
Classification Tree	89.29%	75.00%	93.75%	90.91%	92.86%	96.43%
Support Vector Machine	83.33%	80.00%	84.38%	86.36%	71.43%	89.29%
Naïve Bayes	83.33%	65.00%	89.06%	86.36%	78.57%	96.43%
K-Nearest Neighbor	76.19%	45.00%	85.94%	86.36%	78.57%	89.29%
Discriminant Analysis	82.14%	80.00%	82.81%	81.82%	78.57%	85.71%

The Classification Tree method obtained the best results for accuracy and specificity. The Support Vector Machine and the Discriminant Analysis methods presented the highest sensitivity, however a much lower specificity than the Classification Tree. The Naïve Bayes method achieved the same level of specificity for the normal cases as the one obtained with the Classification Tree method. However, all the other results were lower for the Naïve Bayes method. For the analyzed cases, the classifier K-Nearest Neighbor showed the worst accuracy.

4. CONCLUSIONS

The results obtained with the Classification Tree method strongly suggest the feasibility of the use of thermography as a test for breast cancer. The specificity is considerably high and the sensitivity similar to that of mammography, the standard screening test (Kolb *et al.*, 2002). Furthermore, the high accuracy obtained for the cyst and normal cases indicates that almost only patients with a possible need for surgical intervention will be referred to other investigative and/or invasive examinations. The results also suggest that the segmentation method tested was robust enough to preserve the features here proposed as a method to detect breast cancer. A further study is necessary to clarify the physical origins of the distinctive thermal patterns observed in patients with breast cancer.

5. ACKNOWLEDGEMENTS

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7. RESPONSIBILITY NOTICE

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