

# Digital Processing of Thermographic Images for Medical Applications

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*Breast cancer is the second leading cause of death in women worldwide with an average probability for a woman to develop breast cancer in her life of about 12%. Among the large variety of medical assessment techniques, thermography has attracted attention in applications related to detection and diagnosis due to its capability to provide valuable information on the physiological variations typical of early stages in cancer development thus making possible to diagnose patients in early stages so more thorough examinations can be done in proper time and manner. This paper presents a digital processing approach that allows identification and subsequent isolation of the region of interest in thermograms based texture analysis of the image. This algorithm was tested on case studies thermograms exhibiting different types of cancer and the results showed successful identification and extraction of the region of interest in all cases. Results are presented with different types of cancer in men and women and different image angles showing the robustness of the proposed method.*

*Keywords: breast cancer, digital image processing, thermography*

Breast cancer is the most frequently type of cancer diagnosed in North America. In the United States it has been estimated that 1 in 8 women will develop breast cancer while in Canada the National Cancer institute estimates an incidence of 1 in 9 women with the additional estimate that 1 in 27 women will die of this disease [1-2]. According to the statistics in North America, in 2013 a total of 23,800 women were diagnosed with breast cancer. From this total, 26% of these cases (5,000) were diagnosed for the first time and 14% of the total had fatal ending. On daily average, 65 women will be diagnosed and 14 will die. The situation, however, is also critical for men since on daily average 200 of them men will be diagnosed with breast cancer and 60 will die [1].

The probability of developing breast cancer depends upon a variety of factors. Among these, factors such as age, gender, and genetics are intrinsic and unfortunately cannot be avoided. Nevertheless, there are some typical signatures of the presence of cancer such as tumors and specific tissue activity that the specialists have been using to carry out an early-stage diagnostic.

Tumor activity is a straightforward fingerprint to analyze since it is the major manifestation of a vast group of diseases called *neoplasms*, in other words, different types of *cancer*. Imaging techniques can be naturally used for tumor evaluation i.e. detection, classification, current stage, and diagnosis, due to the massy nature of this pathological process. However, medical diagnosis based only on imaging can be subject to ambiguity due to the fact that many other diseases such as infections produce tumors and, similarly, there a number of infectious agents that cause cancer without a tumor-like manifestation [3].

The typical diagnosis procedure involves radiologists reading batches with a large amount of mammograms. Since only about 0.5% of the analyzed mammogram

images contains breast cancer, it is quite difficult to find the often subtle indications of malignancy on the image. The consequence arises naturally: based on mammography, 5 to 30% of women having breast cancer is mistakenly diagnosed as normal.

In this regard automated diagnosis based on digital analysis of medical images, such as mammograms and thermograms, is an area of great interest in computer science since computerized detection can be a reliable second opinion for radiologists to develop a more consistent diagnosis [4]. Moreover, since these systems are PC based, one is able to store large aamounts of images that can be accessed later in the analysis if needed at the same time that easy management of this amount of information is feasible e.g. interconnection of medical teams and healthcare professionals.

In this paper we present a method that allows performing automatic analysis of thermographs images. Simply put, infrared thermography is an imaging technique that operates on the basis of measuring spatial distributions of temperature. Unlike other common evaluation techniques, like breast mammography, infrared breast thermography allows noninvasive assessment of the physiological functions without involving exposure to radiation and breast compression . The idea of the development of this work is to have a tool that can help to medical diagnosis allowing using automatic processing of thermal images. Results that allow see the viability of the proposed method.

The rest of the article is organized as follows. In section two we present a brief state of the art associated with thermographic images. In section three describes the method proposed in this paper as well as the specifics of the images used.

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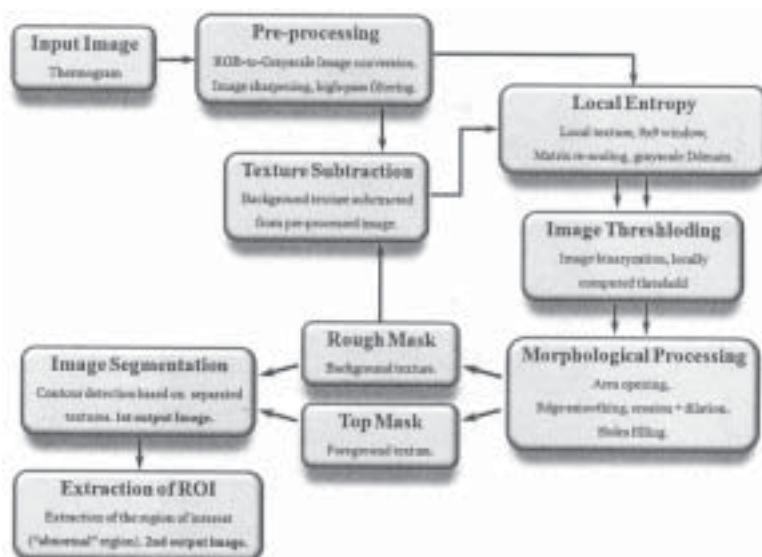


Fig. 1 General schematic of the proposed algorithm

In section four we present the results obtained and the parts of the algorithm used is described in detail. Finally, in Section five presents the conclusions and future work.

## Experimental part

### Thermography

Thermography has proved a useful, inexpensive, and easy-to-use tool in a variety of a medical applications including neurology, oncology, rheumatology, sports medicine, and physical therapy. Thermography-based breast cancer detection has been investigated only over the last few decades and it has been found to be useful since variances in temperature on the surface of the skin, which is strongly related to the presence of a tumor, can be found by imaging the breast and creating temperature profiles [5]. However, the processing of thermograms has to be refined due to its high rate of false positives despite women mistakenly diagnosed are found to be at a high risk of developing breast cancer.

Thermography is extremely powerful in detecting breast cancer in the first year of development, as well as in detecting and recording advanced stages of breast malignancy. Also, the infrared imaging provides subtle and dramatic temperature differences that correlate with various types of breast pathology. We recall that the thermal imaging is also of great importance in monitoring the effectiveness of treatment [6].

At this stage we stress on the fact the thermography differs from the other invasive techniques, e.g. mammography and X-ray, that penetrate the body and producing harmful radiation, whereas thermography is noninvasive and radiation free. We recall that most of the other diagnostic equipment detects the anatomical issues, in contrast with the thermography which investigates physiological patterns. Also, the thermogram, using proper protocol, is able to detect the changes in the skin microcirculation due to the temperature and chemical changes [7]. We have to say that the thermography possess several considerable disadvantages in comparison with other early cancer detection techniques (see for example the mammography). For example its relatively low sensitivity for both deep and small tumors [8-10] and its inability to differentiate the tumors from natural hot spots (e.g., local inflammation), and its reliance as a subjective method on the radiologist's skills to interpret the IR images. Due to these disadvantages as well as other factors, the far thermography failed to get a full acceptance as a primary tool for cancer screening. Infrared breast thermography is a noninvasive procedure, i.e. without

involving breast compression and radiation exposure, that retrieves spatial distributions of temperature. A direct assessment of physiological function and cellular activity in breast tissue can be performed accurately based on the thermal distributions since modern infrared cameras can resolve temperature differences on the order of 0.025°C [10].

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### Method

Figure 1 shows the main stages of the proposed algorithm: input image sharpening, identification of the background texture, identification of the object's texture, and display of the results. The regions of interest are automatic identified and then extracted using both the original input image and the background texture as a contrast mask. This means that what it is identified as an abnormal region in the top mask stage depends on what was previously identified as the background region in the rough mask stage.

In this sense, understanding that image sharpening as a pre-processing stage is used only to enhance the details in the input image, the stages related to the back-ground/object's texture segmentation and extraction become the most important within the process. The process in this stage starts with the calculation of the local entropy of the image. Entropy is the measure of the information content in a probability distribution. For digital images the probability distribution is represented by the histogram of gray values [13]. If an image consists of  $N$  possible gray values whose actual frequencies of occurrence (i.e. the normalized image histogram values) are  $p_1, p_2, \dots, p_N$ , the entropy of the image is defined as

$$H = -\sum_{k=1}^N p_k \log_2(p_k) \quad (1)$$

With local entropy, the entropy of each pixel is computed

individually by means of the gray values of the local neighborhood. This stage has two inputs: the high-pass filtered image and the gray value of the threshold. The latter is an input variable of the global process. According to the first-order processing mentioned above, a window size of  $9 \times 9$  was used to compute the local entropy and then extract the properties of the local textures based only on the adjacent neighbors of the current pixel of the image. The next stage consists of obtaining a binary image via thresholding.

Once the image has been thresholded, a primitive version of the background texture mask is available. However, this image cannot be used for further processing yet. It is worth mentioning that after thresholding, the image remains as a binary image, which means that the textures are treated as binary region masks instead of treating them as gray scale regions.

A feature of an image (e.g. luminance, tristimulus value, spectral value) is a distinguishing primitive characteristic or attribute of an image. Some of them are natural, namely such features are defined by the visual appearance of an image. Some other, artificial features result from specific manipulations of an image. Natural features include the luminance of a region of pixels and gray scale textural regions. Image amplitude histograms and spatial frequency spectra represent examples of artificial features. The image features are fundamental in the isolation of regions of common property within an image (segmentation) and subsequent identification or labeling of such regions (classification). In a given thermal image, we can distinguish a diagram of different temperatures in a body. Each color corresponds to a temperature. These temperature changes precisely i.e.  $\Delta T \approx 0.025^\circ\text{C}$ , and this high resolution temperature map can be represented through the corresponding color image. And this is what we take advantage to identify the texture of the area of the lesion zone on the image then finalizing the extraction of the same [11].

The area opening stage consists of removing the "small" objects from the binary image to clean the background texture. To follow the transition regions more approximately, edge smoothing is performed by a sequential process of dilation followed by erosion using a square mask of dimensions  $9 \times 9$ . Finally, isolated background pixels are connected, filling the holes within the background texture. Once this process has been completed, a binary image containing the background texture mask is available for further stages. The background texture mask obtained at the end of this stage is only a partial result that will be used for further processing.

The next stage, in which the object's texture is identified and then both the background and object's textures are separated, has two inputs: the original input image and the binary image of the background mask obtained in the previous stage. Texture analysis is performed over the non-background region by computing the local entropy with a similar window as that used in the previous stage. The disregarded region of the original image (background) does not contribute to further results, as the local entropy is minimal for regions consisting of pixels with the same gray value [13-14].

Unlike the previous stage, the thresholding of the non-background region in the current stage is performed using a locally computed threshold considering the image where the background is disregarded. The morphological treatment of the binary image obtained after thresholding is similar to that performed in the previous stage. Once the binary mask of the object's texture is obtained, both regions

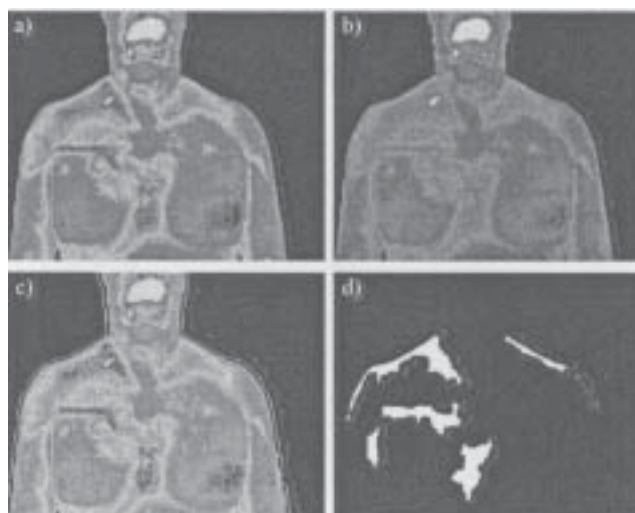


Fig. 2 Breast cancer in men. a) Pseudo-coloured image, b) gray-scale image, c) segmented image, and d) extracted image.

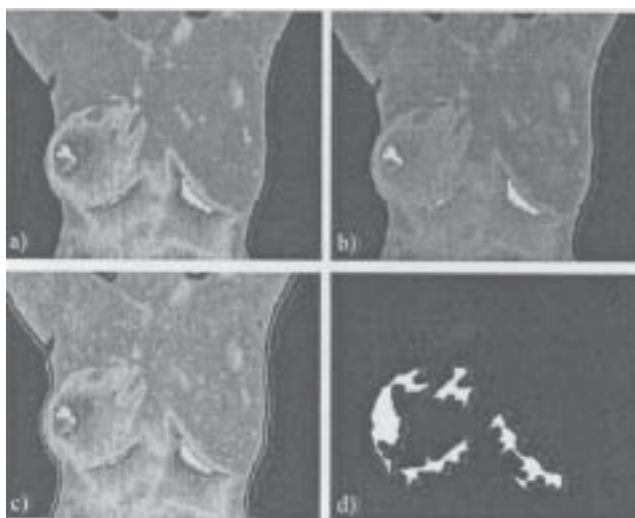


Fig. 3 Process thermogram of medial left breast in women, a) Pseudo-coloured image, b) gray-scale image, c) segmented image, and d) extracted image

and their contours can be reconstructed and displayed.

## Results and discussions

When the image is processed, the purpose is to extract the ROI, as described in figure 1. To make this extraction is required to image segmentation and subsequent extraction.

For proper removal, it is required image quality (without additional marks that alter the result). Correct processing of these images allow tracking the lesion in a patient over time and seeing if, given the impact it has had in treating the patient.

In this paper the results are presented with images and breast cancer in men, as it is mentioned in figure 2. A case of cancer also occurs in the middle part left in woman, which also, in this case, the image is presented in a different angle thus allowing to see the benefits of the proposed method does not depend on a particular image position (fig. 3).

The images used in this work were taken with the permission of the hospital: Miami Holistic center (<http://www.miamiholisticcenter.com>). Are three images of breast cancer in female (fig. 3, 4 and 5) patients and one case of breast cancer in a man (fig. 2).

In both images can be seen the segmentation process performed and the extraction of the region of interest. The idea of implementing this tool is to allow the doctor to give a temporary track in the same manner and measure the



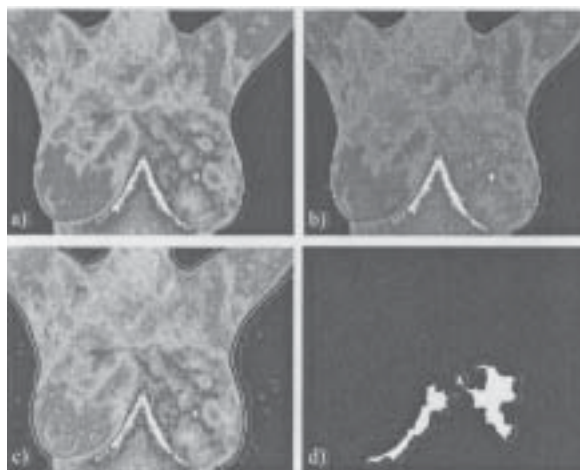


Fig. 4 Process thermogram of medial left breast in women, a) Pseudo-coloured image, b) gray-scale image, c) segmented image, and d) extracted image

impact it has had on the patient and a specific treatment plan accordingly how best patient intervention. This system is based on the automatic detection of regions of interest considering the texture of the image as described in the method.

This information can be useful to automatically classify images and help so that the physician has more elements when making a medical diagnosis.

### Conclusions

Breast cancer is a disease that needs to be caught early, but many women may deter from being examined due to economic factors, lack of convenience and discomfort with traditional exams such a mammograms. Thermography is an affordable option that is easy to run and causes minimal distress to the patient. Mammograms are known to cause pain and while they are and effective means of detection, their use can be minimized by thermograms. If thermography can get to a point where it is reliable enough to indicate the lack of a tumor confidently, then the need for a mammogram would be eliminated. If the thermogram indicated a possible tumor, then a mammogram could be conducted as the next step to either confirm or reject the claim. Such an option may make women more inclined to be examined for cancer if the hassle and discomfort were eliminated from the procedure.

Future studies can be performed to further determine if thermograms provide accurate enough results, and if so, what kind of error they produce. Different factors such as variations in ambient air temperature, air flow around the breast, whether the patient is sitting up or lying down, density of the breast and cysts can all be considered in their effects on surface temperature.

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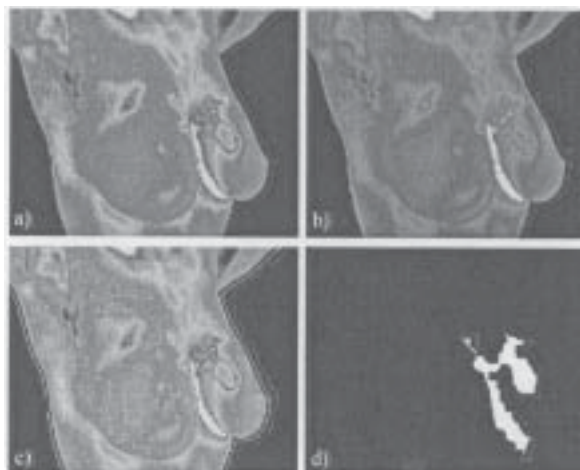


Fig. 5 Process thermogram of medial left breast in women, a) Pseudo-coloured image, b) gray-scale image, c) segmented image, and d) extracted image.

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