# Digital Breast Thermography Processing for Breast Cancer Detection

**Rafael Guzmán-Cabrera**
University of Guanajuato, México
DICIS, Universidad de Guanajuato, México
Km. 3.5 + 1.8 Carr. Salamanca-Valle de Santiago, Salamanca Gto. Mexico
E-mail: guzmanc@ugto.mx

**José Rafael Guzmán Sepúlveda**
CREOL, The College of Optics and Photonics, University of Central Florida
4304 Scorpius St., Orlando FL 32816-2700
r.guzman@knights.ucf.edu
(407) 823 6845

**Abstract**

One in eight deaths worldwide is caused by cancer. Cancer is the second leading cause of death in developed countries and the third leading cause of death in developing countries. In the United Sates, cancer is the second most common cause of death, and accounts for nearly 1 of every 4 deaths. The chance of developing invasive breast cancer at some time in a woman's life is about 1 in 8 (12%). Thus, the incidence and mortality of breast cancer are very high, so much so that breast cancer is the second leading cause of cancer death in women.

Although breast thermography has its limitations, namely in sensitivity, specificity and its dependency on examination conditions, it provides valuable information about the physiological condition of the breast. Its ability to detect early physiological changes in the breasts due to cancer formation can be used to identify patients that require more thorough examinations, thus making subsequent treatment more effective.

This paper presents a digital thermography approach for detecting early stage tumors. The implemented algorithm is absolutely capable of identifying and subsequently isolating the area of interest taking into consideration the result of the texture analysis of the image. The proposed technique shows better results. The method was tested over several images. Results enable us to see the effectiveness of the proposed method.

**Keywords:** Breast Cancer, Digital Image Processing, Thermography

## 1. Introduction

Breast cancer is the most frequently diagnosed cancer in North American women. The National Cancer Institute of Canada estimates that 1 in 9 women will develop breast cancer in their lifetime and 1 in 27 will die of the disease [1]. The statistics of the United States are similar with an incidence estimated to be 1 in 8 women developing breast cancer [2]. The probability of developing breast cancer increases with age and the leading risk factors associated with the development of breast cancer, specifically age and gender, is not modifiable.

People with tumors or potential tumors are imaged for detection, classification, staging, and comparison. The term "tumor, " which literally means swelling, can be applied to any pathological process that produces a lump or mass in the body. Tumors are a major manifestation of a vast and varied group of diseases called neoplasms, or more commonly referred to as cancers. However, many other diseases such as infections can produce tumors, and they are a source of confusion in imaging diagnosis. Detection of tumors can be subdivided into diagnosis, case finding, and screening, depending on the level of suspicion. People are usually referred for diagnosis because they have signs and symptoms suggestive of cancer [3].

Radiologists read screening mammograms in batches, sometimes 100 or more at one sitting. Only about 0.5% of these cases will have breast cancer, therefore it can be hard to remain vigilant enough to find the often subtle indications of malignancy on the mammogram. Consequently, between 5% and 30% of women who have breast cancer and a mammogram are wrongly diagnosed as normal. Computerized detection of breast lesions can be used by radiologists as a “second opinion” thereby reducing the chances that a cancer is missed. Therefore, automated analysis of mammograms and thermography images is the most active area in computer diagnostic research [4].

Thermograms have been researched for several decades but are still being refined due to their high rate of false positives. However, women with false positives have been tried and found at a high risk of developing breast cancer. By imaging the breast and creating temperature profiles, variances in temperature on the surface of the skin can show the presence of a tumor [5].

Thermography is exceptional in detecting breast cancer within the first year of progress, as well as detecting and recording more advanced stages of breast malignancy. Infrared imaging shows subtle and dramatic temperature differences that correlate with various types of breast pathology. Thermal imaging is also of great value in assessing the effectiveness of treatment [6].

Thermography is different than other invasive techniques, such as mammography and
X-ray that penetrate the body with harmful radiation, whereas thermography is noninvasive and radiation free. Most other diagnostic equipment detects anatomical issues, but thermography researches physiological patterns. The thermogram, using the proper protocol, detects changes in the skin microcirculation as a result of temperature and chemical changes [7].

Thermography as a breast cancer risk assessment tool in the US was subject to approval by the FDA since 1982, and as a screening tool for breast cancer, thermography was first introduced in 1956 and was accepted widely by medical professionals at that time [8]. However, this acceptance rapidly ended in 1977 after a report written by Feig et al. [9] tested the sensitivity of thermography compared to other methods of breast cancer detection. The results of this study, in the Breast Cancer Detection Demonstration showed that thermography came out third, after ultrasound and mammography, with a sensitivity of only 39% and a specificity of 82% [9].

Thermography can offer several considerable advantages: it is radiation and contact free, and it is a relatively low-cost approach. However, thermography has several considerable disadvantages when compared to other early cancer detection methods (e.g. mammography), including its relatively low sensitivity for deep and small tumors [10], its inability to distinguish 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. Thus far, thermography has failed to gain full acceptance as a primary tool for cancer screening because of these disadvantages and other factors.

The detection of changes in the appearance of the breast, or in the appearance of potential lesions that are being watched mammographically over time for changes in appearance, is also of great interest to mammographers and those developing CAD techniques. The human visual system is very good at detecting change, but subtle differences in size or shape can be difficult to detect, especially because subtle changes require that attention be focused on the locus of change. Lapses in attention or distractions, which often occur in reading rooms, can result in subtle lesion changes being missed. A computer does not suffer from lapses in attention or distractions, so changes in lesion shape or size might be more reliably detected using CAD schemes designed for this purpose [11].

In this paper, we present a method that details the automatic analysis of thermography images. The idea behind the development of this work is to get a tool that can help in medical diagnosis, allowing automated processing of thermal images. Results show the viability of the proposed method.

The rest of the paper is organized as follows; section two describes the method proposed in this work as well as the specifics of the images used. In section three, we present the results obtained by giving details of the parts of the algorithm used. Finally in section four of the conclusions and future work are to be submitted.

## 2. Method

Breast infrared thermography is a noninvasive procedure that does not involve compression of the breast tissue or exposure to radiation, and functions through an assessment of physiological function, through high resolution temperature measurements of breast tissue.

Infrared radiation is emitted from objects with a temperature above absolute zero [3,4]. The human body radiates heat energy from the surface of the skin and the emissivity of human skin is 0.98, which is close to that of a perfect black body [5]. Infrared thermography is the recording of temperature distribution of a body using the infrared radiation emitted by the surface of that body at wavelengths between 0.8 µm and 1.0 µm [6]. An infrared camera is used to detect the infrared heat energy that is emitted from the skin. The amount of energy that is recorded is converted into an energy signal that, along with other parameters, is used to calculate the actual temperature of the object. With this information it is possible to create a visual map or thermogram of the distribution of temperatures on the surface of the object, imaged [5]. The sensitivity of modern infrared cameras is such that temperature differences to 0.025 ℃ can be detected [3]. Breast infrared thermography is a noninvasive procedure that does not involve compression of the breast tissue or exposure to radiation, and functions through an assessment of physiological function, through high resolution temperature measurements in breast tissue.

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 automatically 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.

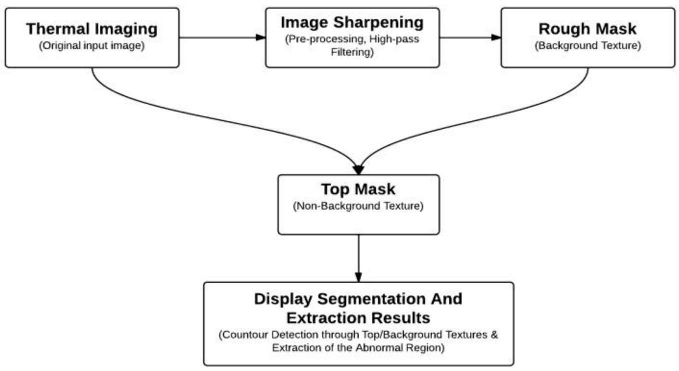


**Figure 1. General schematic of the proposed algorithm**

In this sense, understanding that image sharpening as a pre-processing stage is used only to enhance the details in the input image, stages related to the background object’s texture segmentation and extraction become the most important within the process. They will be further explained in more detail.

Many portions of images of natural scenes are devoid of sharp edges over considerable areas. In these areas, the scene can often be characterized as exhibiting a consistent structure analogous to the texture of cloth. Image texture measurements can be utilized to segment an image and classify those segments. Several authors have attempted to qualitatively define texture [10].

Figure 2 shows the internal structure of the stage where the background texture is identified and then extracted. The process in this stage starts with the calculation of the local entropy of the image.

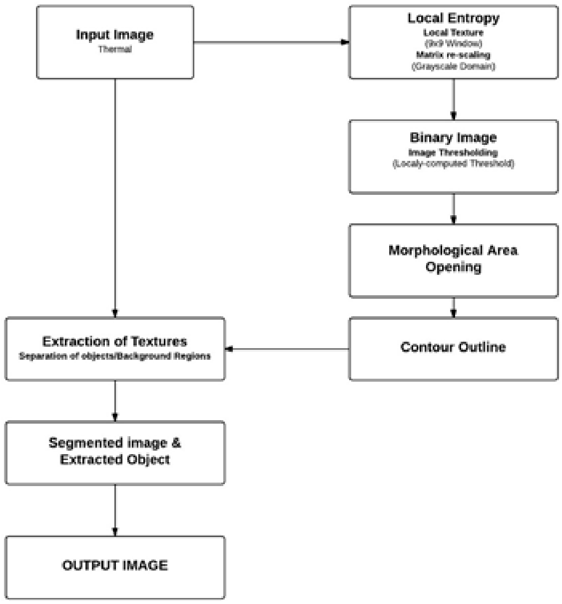


**Figure 2. Internal structure of the stage where the background texture is extracted**

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 [12]. If an image consists of N possible gray values whose actual frequencies of occurrence (i.e. the normalized image histogram values) are $p_1$, $p_2$ … $p_N$, 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 × 9 was used to compute the local entropy and then extract the properties of the local textures based only on the adjacent (surrounding) neighbors of the current pixel in 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.

An image feature is a primitive distinguishing characteristic or attribute of an image. Some features are natural in the sense that such features are determined by the visual appearance of an image, while 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 are examples of artificial features. Image features are of great importance in the isolation of regions of common property within an image (image segmentation) and subsequent identification or labeling of such regions (image classification).

The most basic of all image features is some measure of image amplitude in terms of luminance, tristimulus value, spectral value or other units. There are many degrees of freedom in establishing image amplitude features. Image variables such as luminance or tristimulus values may be utilized directly, or alternatively, some linear, nonlinear, or perhaps non-invertible transformation can be performed to generate variables in a new amplitude space. Amplitude measurements may be made by specific image points, e.g., the amplitude F(j,k) at pixel coordinate (j,k), or over a neighborhood centered at (j,k). For example, average or mean image amplitude in a WxW pixel neighborhood is given by

$$M(j,k) = \frac{1}{W^2}\sum_{m=-w}^{w}\sum_{n=-w}^{w} F(j+m, k+n) \quad (2)$$

Where W = 2w + 1. An advantage of a neighborhood, as opposed to a point measurement, is a diminishing of noise effects because of the averaging process. A disadvantage is that object edges falling within the neighborhood can lead to erroneous measurements. The median of pixels within a WxW neighborhood can be used as an alternative amplitude feature to the mean measurement of Eq. 1, or as an additional feature. The median is defined to be that pixel amplitude in the window for which one-half of the pixels is equal or smaller in amplitude, and one-half are equal or greater in amplitude. Consequent stages constitute the morphological treatment of the image and identify the final version of the background texture.

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 ×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.

## 3. Results

Segmentation of the breast tissue area is a step that is common to almost any breast image-processing technique. An obvious reason for initial labeling of the breast tissue area is the gain in computational speed, which can be achieved by avoiding time-consuming lesion detection operations to process the image background. Moreover, generation of false alarms outside the breast, for instance caused by film identification markers, should be avoided in practice to prevent the radiologist losing confidence in CAD. The necessity of knowing where the breast tissue boundary is located is also required by many mass detection algorithms to avoid inaccurate results caused by kernels overlapping the background or to warp corresponding images taken from different screenings of the same patient.

Figure 3 shows five images in which you can see the sequence algorithm implemented from the input image to results in the output image. In this case, the images correspond to a case of breast cancer in men. Since this analysis is non-invasive, potentially can allow a physician to monitor a patient with respect, for example, the effect it has had a certain medication or specific treatment to be able to check the evolution or decrease of the lesion in the patient.

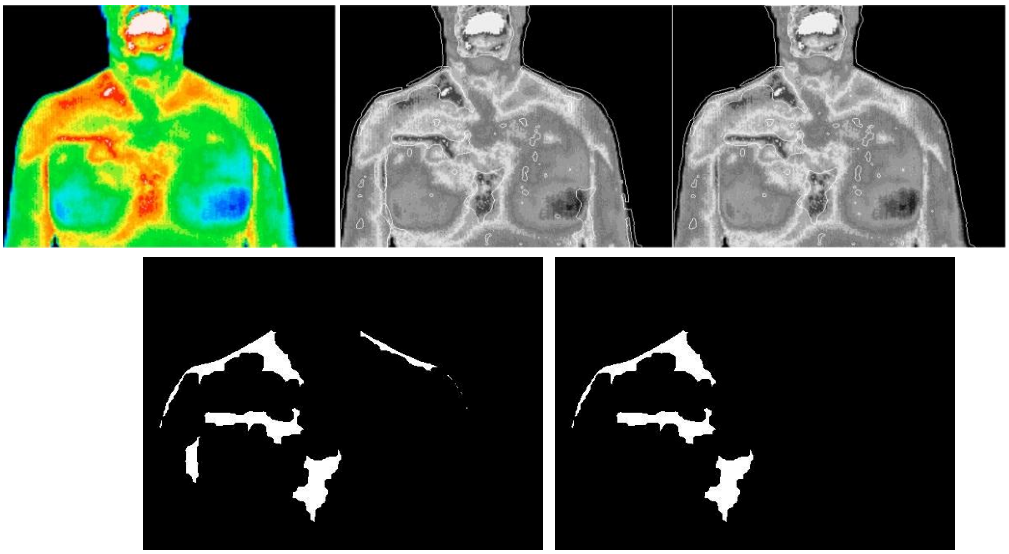

**Figure 3. Proposed method test in a case of breast cancer in man**

You can see the segmentation process performed and the extraction of the region of interest. The idea of implementing this tool is to allow the doctor to analyze a provisional record in order to measure the impact on the patient and to intervene with a specific treatment plan according to each patient. 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 utilized to automatically classify images and so the physician has more elements when making a medical diagnosis.Other results obtained on a processed image are shown in Figure 4 and 5, as can be seen in the proposed method is useful for detection and removal of potentially injury areas helping to improve medical diagnosis.

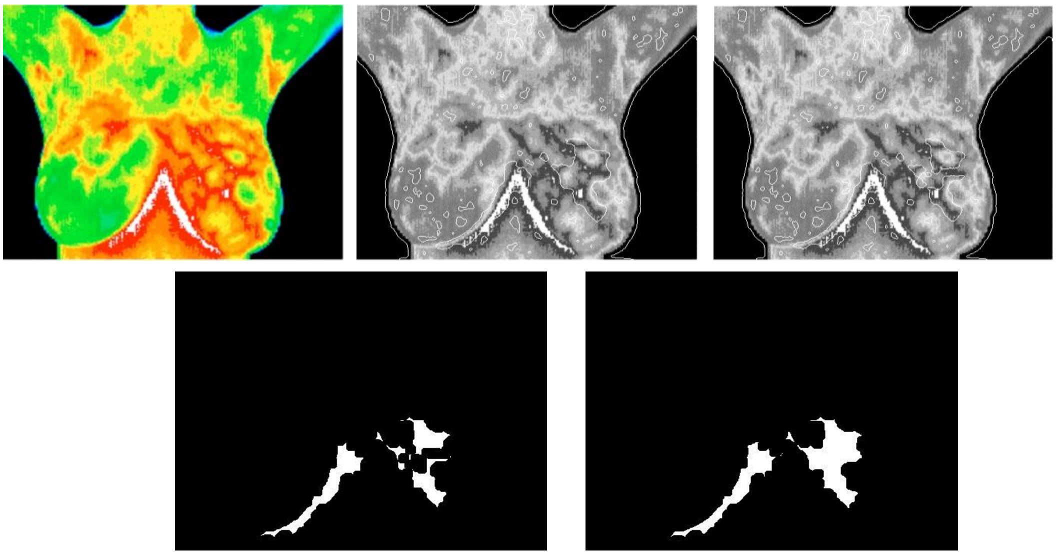

**Figure 4. Proposed method test in a case of breast cancer in women 1**

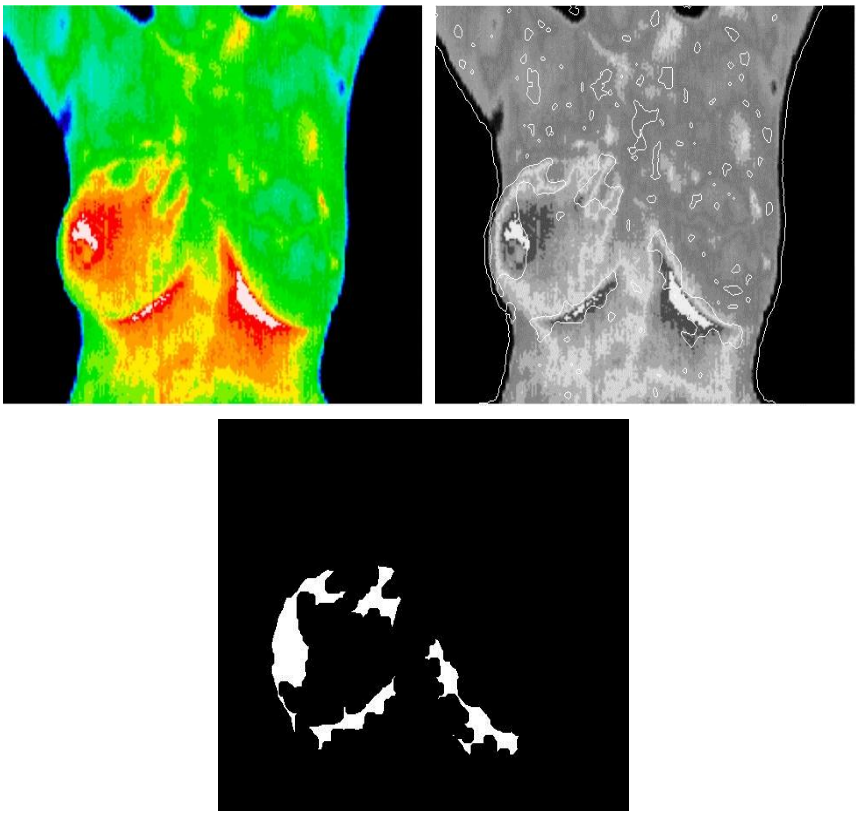

**Figure 5. Proposed method test in a case of breast cancer in women 1**

## 4. Conclusions

The potential for CAD is immense. It should prove to be an important aid to mammographers in the near future. As noted, the main factor inhibiting its wide scale use in the mammography clinic is that all the mammography films have to be digitized before CAD systems can analyze them.

Breast cancer is a disease that needs to be caught early, but many women may be deterred from an examination 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 an effective means of detection, their use can be minimized by thermograms. If the thermogram indicated a possible tumor, then a mammogram could be conducted at the next step to either confirm or reject the claim. If thermography reaches a point where it is reliable enough to indicate the lack of a tumor confidently, then the need for a mammogram would be eliminated. Such an option may make women more inclined to be considered for cancer if the hassle and discomfort were eliminated from the procedure.

Further studies should 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.

In future work on automatic image classification (with/without tumor), using elements of training images manually labeled by experts will provide the required knowledge to perform the classification task.

## References

*[1] Canadian Cancer Society/National Cancer Institute of Canada. Canadian cancer statistics 2007. www.cancer.ca or www.ncic.cancer.ca. Accessed November 14, 2012.*

*[2] National Cancer Institute. Probability of breast cancer in American women. http://www.cancer.gov/cancertopics/factsheet/Detection/ probability-breast-cancer. Accessed November 14, 2012.*

*[3] Bronzino JD. Medical Devices and Systems. Boca Raton, FL:CRC/Taylor & Francis; 2006.*

*[4] Jones BF. A reappraisal of the use of infrared thermal image analysis in medicine. IEEE Trans Med Imaging. 1998;17:1019-1027.*

*[5] Diakides NA, Bronzino JD. Medical Infrared Imaging. Boca Raton, FL: CRC Press; 2008.*

*[6] Ring EFJ. Thermographic terminology. Acta Thermographica. 1978:1-30.*

*[7] Chapman G, Britt B, Lea V. "Focus on Thermography Symposiums." Presented by CTA as part of an on-going seminar series, 1978-2010.*

*[8] Moore G. Breast cancer: early detection needed. Bus Health. 2001;19:39.*

*[9] Feig SA, Shaber GS, Schwartz GF, et al. Thermography, mammography, and clinical examination in breast cancer screening. Review of 16,000 studies. Radiology. 1977;122:123-127.*

*[10] 4. William CA. Infrared imaging of the breast. In: Bronzino JD, editor. Medical devices and systems. The biomedical engineering handbook. 3rd ed. Boca Raton (FL): CRC Press; 2006.*

*[11] S Sanjay-Gopal, H Chan, B Sahiner, NA Petrick, TE Wilson, MA Helvie. Evaluation of interval change in mammographic features for computerized classification of malignant and benign masses. Radiology 205(P):216, 1997.*

*[12] Zambanini S. and Kampel M. Segmentation of Ancient Coins Based on Local Entropy and Gray Value Range, Computer Vision Winter Workshop 2008*