The ISC Int'l Journal of Information Security

November 2020, Volume 12, Number 3 (pp. 73–79)

http://www.isecure-journal.org

Selected Paper at the ICCMIT'20 in Athens, Greece

Fuzzy Histogram Equalization and Computer Vision Automated Identification of Microcalcifications in Breast Cancer**

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ARTICLE INFO.

Keywords:
Fuzzy Histogram Equalization, Computer Vision, Automated Identification, Microcalcifications Breast Cancer

Type: Research Article

doi: 10.22042/isecure.2021.271062.616

ABSTRACT

Simple signs existent in mammograms for diagnosing breast cancer are considered to be microcalcifications or MCs. Therefore, true detection of MCs is needed to minimize schedule diagnosis, efficient care and death rate due to breast cancer. A challenging task is to evaluate and interpret mammograms and, more over to the poor contrast consistency of MCs relative to the remain of the tissue, the precise identification of MCs, such as the minor size and random shape and size of the MC clusters, has several obstacles. These restrictions in the manual analysis of MCs increase the demand for an automated recognition system to help radiologists in mammogram analysis and it is important to design strength algorithm for this purpose. The goal of this paper is to present an efficient procedure that can be used to enhance images for extracting features to give excellent classification. The classifier senses which the region was normal, benign or malignant. The performance of KNN classifier with fuzzy histogram equalization using Otsu's multi threshold segmentation give excellent results in detection and recognition in mammograms for breast cancer distinguished in image mammograms obtained from hospital.

1 Introduction

One of the well-known forms of cancer is breast cancer among females with diverse death rates in several locations around the World. It is hard to diagnose breast cancer on time, much like certain other forms of cancers. Therefore, diagnosis before advanced symptoms occur plays a significant part in improving the rate of survival, the living environment of the patient and the prognosis [1]. In the past forty years, a variety of different screening methods, such as sonography and mammography, have been used for the early detection of breast cancer. Mammography is considered to be the most effective of the numerous diagnostic methods currently available for the identification of both benign and malignant mammary neoplasia at early stage cancer prognosis [2, 3]. Radiologists also use mammography scans today, also with regular screening programs. Malignant cancer is characterized by the presence of MCs as grouped allocations and single MCs typically denote to benign cancer [4, 5]. Microcalcifications are tiny deposits of calcium in the breast tissue that are present. Sub-

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**The ICCMIT'20 program committee effort is highly acknowledged for reviewing this paper.

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ISSN: 2008-2045

sequently, these MCs perform on an inhomogeneous backdrop as tiny light spots in a mammogram. It is important to check their classification according to their natural such as shape, size, and density, number of MCs and pattern of distribution in order to distinguish MCs into malignant and benign classes [6]. According to benign cancer, MCs have diameters ranging from 1 to 4 mm and can be circular or ovular in form, coarse or textured, and might have distribution patterns that are scattered or diffused individually. Malignant microcalcifications usually show distributions in clusters of not more than 0.5 mm in diameter and a pattern of linear prototype of more than 3 MCs together. There are stellar models in various shapes and dimensions [7]. However, there is an issue of false negative detections lead to the poor contrast feature of the mammogram images, which means that certain obscure anomalies are likely to be eliminated. The image quality can also rely on the patient's age, physical and hormonal conditions [8]. The fast progress in image processing and artificial intelligence in recent years has led to different perspectives for mammogram research. To help radiologists read and diagnose cancer mammograms, computer-aided detection (CAD) systems are also utilized. It was approved in 1998 by the FDA [9]. To increase the precision of cancer detection [8, 10, 11], this automated system has proved to be more effective. The large risk of human error is therefore decreased. Clinicians check mammograms manually to assess the existence of MCs, malignant tissues and skin thickening for diagnostic purposes. This was the only available choice in the earlier. In order to aid the study of mammograms with diverse stages, various scientists have now suggested their own respective algorithms, which can be used to check or confirm the diagnosis. Many methods have been studied by various investigators. Sophisticated tools that integrate these features lead to precise detection and classification [12–14]. Many other approaches, for instance wavelet transformation, various filtering techniques, morphological transformation, mathematical, histogram equalization, neural networks, fuzzy logic, texture analysis and support vector machine (SVM), have been studied at diverse phases of breast cancer recognition [15–17]. In order to modify the image histogram in such a way that no remapping of peaks takes place, brightness preserving dynamic fuzzy histogram equalization is used. It evenly redistributes the histogram values between two consecutive peaks only in valley areas. [18]. The algorithm of Otsu's has been implemented for microcalcification segmentation from a mammogram image. To evaluate the threshold value, Otsu's algorithm computes over all threshold values where at its lowest, with maximum interclass variation, the number of foreground and background ranges [18]. KNN classification was done to detect benign/malignant calcifications [19, 20].

2 Dataset

In this work some samples of MIAS database (fatty, dense and glandular tissue mammograms) have been used. The type of image is PGM and its size 1.00 MB for each image.

3 Methodology

There are 3 stages of calcification detection from mammogram images:

1. In the first stage, the mammogram's contrast is enhanced to bring out the minor changes in muscle intensity. In this step, the details unseen by the human eye, are highlighted.
2. In the second stage, segmentation operations of different natures are performed on the image to visualize the calcifications.
3. Detection and recognition of calcifications. Figure 1 shows the flowchart of calcification detection.

3.1 Fuzzy Histogram Equalization

The equalization of the dynamic fuzzy histogram does not change the brightness and arranges the image of the histogram in a manner that maps the peaks and they will not emerge again. Histogram values are readjusted in a standard manner between valleys, spaces with two peaks in series, like. The equalization of the fuzzy histogram is broken down into the following steps [21]:

1. Fuzzy Histogram Computation
2. Histogram Partitioning
3. Dynamic Histogram Equalization of the Partitions
4. Normalization of the brightness of the image
5. Fuzzy Histogram Computation

Three phases in the fuzzy process are involved. In the first image coding, new values such as brightness, homogeneity or edginess are given regarding the properties of the image. Next, after image conversion to fuzzy plane, optimum values are generated for them by fuzzy approach. The output of the fuzzy plane is decoded in the last step to acquire a modified gray level. It implies that a value that is based on its location in the histogram is given to each gray level. Dark pixels are given low values and height is given to bright ones. The brightness and contrast are qualitative properties of the image. For the histogram operation process, histogram equalization can be used. A fuzzy histogram is a group of real numbers that are given by $h(i), i \in \{0, 1, \ldots, L-1\}$ where $h(i)$ is the incidence frequency of the gray levels "around i". The gray value I(x,y) is

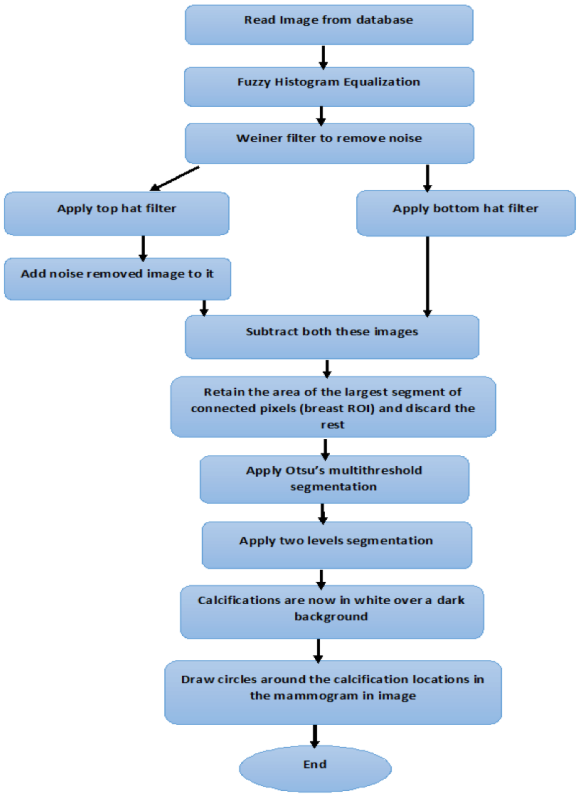


Figure 1. The flowchart of calcification detection

known to be a fuzzy number $\tilde{I}$(x,y). Fuzzy histogram is then calculated as Equation 1 [21, 22]:

$$h(i) \leftarrow h(i) + \sum x \sum y\mu(x,y)i, k \in [a,b] \qquad (1)$$

Here $\mu_{-}(\tilde{I}$(x,y)i) is function of triangular fuzzy membership and the [a,b] are the support points of the membership function.

3.2 Histogram Partitioning

Histogram partitioning based on local Maxima, in order to get several sub-histograms, is done in the stage. This method forms a partition of each valley section between two local maximums. The peaks of the histogram are not altered when the dynamic equalization of these partitions is done and these results are enhanced the preservation of the mean image brightness and increasing the contrast as in [21].

3.3 Dynamic Histogram Equalization of the Sub-histograms

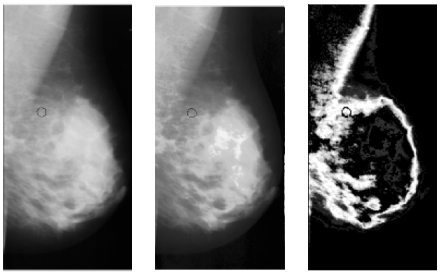
By the DHE process, the collected sub-histograms are separately equalized. The equalization approach utilizes a spanning function constructed on the whole pixels number in the sub part. It requires two operating stages, specifically matching each part to a dynamic range and equalize the histograms [21].

3.4 Normalization of the Brightness of the Image

Output brightness is diverse from the input image is the image acquired after histogram equalization for each sub histogram. The method of normalization is applied to the output image in order to eliminate this change. Let m_i and m_0 be the mean brightness levels of the input image and the image f were found after dynamic histogram equalization phase. When g is the output image of BPDFHE method and the gray level value for the pixel location (x,y) in the image g as Equation 2 [21]:

$$g(x,y) = \frac{m_i}{m_0} f(x,y) \qquad (2)$$

This method of maintaining brightness guarantees that the average intensity of the image created after the procedure is the equivalent as same the input. Figure 2 shows the results of BPDFHE.



(a) (b) (c)

Figure 2. (a) The original image, (b) The resulted image after BPDFHE, and (c) The resulted image of subtracted input image from output Image

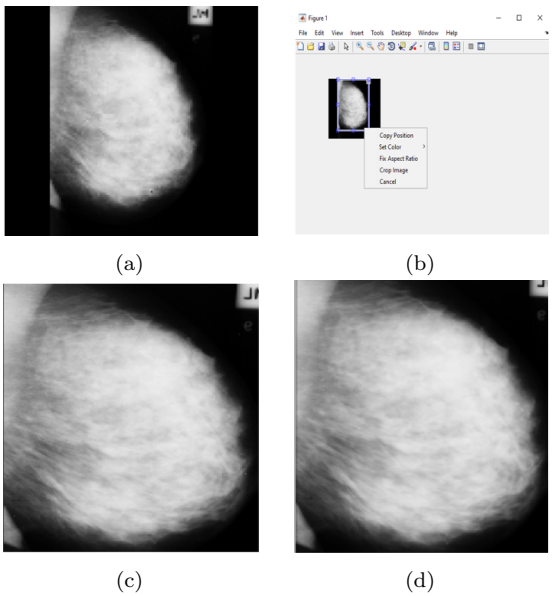
3.5 Wiener Filtering

Many studies have suggested that Wiener filtering is useful for the initial noise reduction process for identification the breast cancer. In state inverse filtering and noise smoothing, this filtering approach is the best according to MSE or mean square error measurements. A linear estimate of the real image can be assumed. It is built on a basis of stochasticism [23, 24]. The Fourier domain Wiener filter is described as follows:

$$W(F_1,F_2) = \frac{H(f_1,f_2)Sxx(f_1,f_2)}{2|H(f_1,f_2)|Sxx(f_1,f_2) + Snn(f_1,f_2)} \qquad (3)$$

where $Sxx(f_1,f_2), Snn(f_1,f_2)$ and $H(f_1,f_2)$ are power spectra of actual image, additive noise and blurring filter, respectively.

First, the image have been read, and removed noise from it using Weiner filter. Then the user will draw a bounding box around the breast. This step had to be included to make sure that even if images of some



(a) (b) (c) (d)

Figure 3. (a) The original image, (b) Identify the ROI of breast, (c) Cropped image, and (d) Resulted image after wiener filter

different format (where the label tags were differently arranged) are given to the program, it can successfully do detection. Figure 3 shows the resulted image after wiener filter.

3.6 Top and Bottom Hat Filtering

The extracted noise from image was restored to the filtered image of the top hat. The resulting image was subtracted from the filtered image of the bottom hat. The result image has been reflected the major part of related component pixels to be the region of interest that is breast and discarded the other areas. The basic aim of enhanced image is to improve the disparity between normal and abnormal tissues so that the mammogram can be interpreted more clearly by the radiologist [25]. Enhanced image strategies contain contrast modulation, reducing noise, and ROI edge or border sharpening [25–27]. To raise the bright pixels, a top hat filter (opening) is used as shown in equations below:

$$(I \circ S) = (1 \ominus S) \oplus S \quad \text{opening} \tag{4}$$

To improve the dark pixels, a bottom hat filter (closing) is used

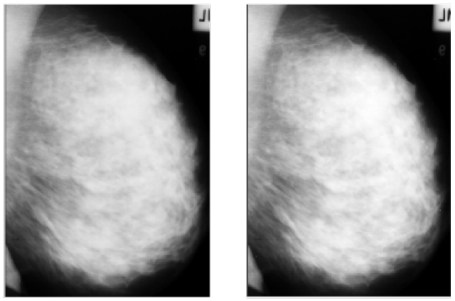
$$(I \bullet S) = (1 \oplus S) \ominus S \quad \text{closing} \tag{5}$$

$$TH = I - (I \circ S) \tag{6}$$

$$BH = (I \bullet S) - I \tag{7}$$

$$C = 1 + (TH - BH)$$

The area of interest (ROI) is this chosen area. Figure 4 shows resulted image after top and bottom filtering.



(a) (b)

Figure 4. (a) After subtracting top and bottom hat, (b) Enhanced breast region

Figure 5. Tow level segmentation (microcalcification in white)

3.7 Segmentation

In segmentation, to isolate the object of interest, the input image is separated into regions that do not overlap. Multi-threshold segmentation (Otsu's method) is applied. MCs are considered highlighted in the segmented image above and the black area is background. This method creates clustering build on finding the threshold in image automatically[27]. In this work after applying top and bottom hat, the next step is Otsu's method have been applied. Otsu's method calculates the best satisfactory threshold which it splits the pixels into two areas, so the difference in inter class is maximum. Following this a two level segmentation will be done. The binary image is output from this process which has microcalcifications in white pixels and the remainder of the black pixels. Figure 4 shows the resulted image after two levels segmentation. As a final step, we plot circles around the microcalcifications which are exist in the original enhanced image as shown in Figure 5.

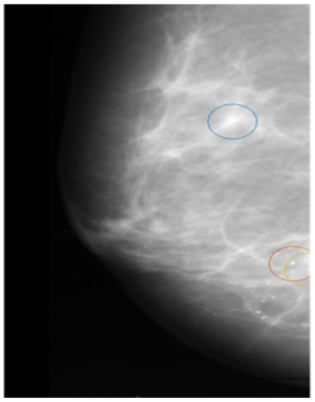
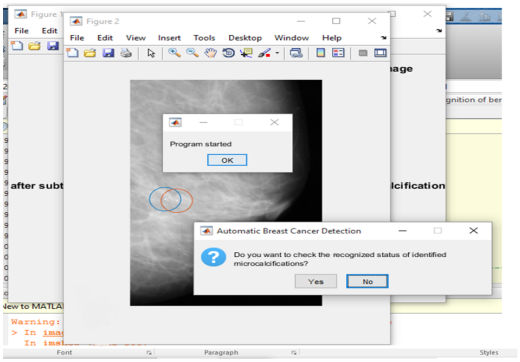


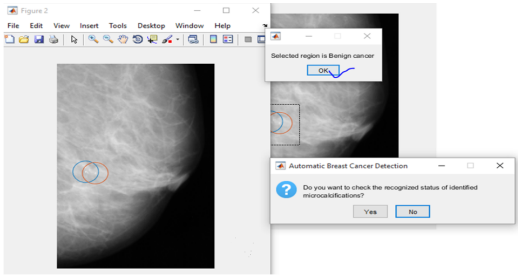
Figure 6. Tow level segmentation (microcalcification in white)

4 Recognition

At this point, the user will be asked to make a bounding box around the region that it is selected to examine and the program gives results of this selection as shown in Figure 6. If the selected area is a normal region then the results as shown in Figure 7.



(a)

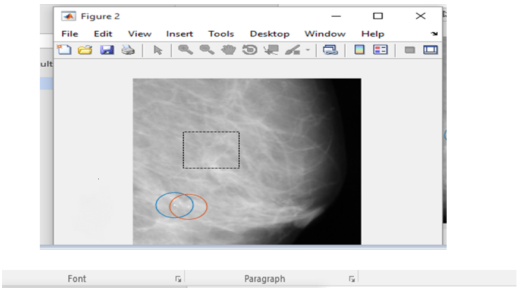


(b)

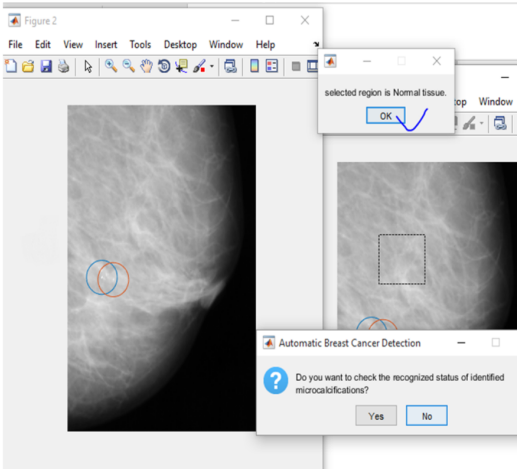
Figure 7. (a) Check of recognized status of identified the microcalcifications, (b) The results of selection

4.1 Textural Feature Extraction

Three different methods for extracting features have been used to remove the textural characteristics of the images, GLCM (gray-level co occurrence level), kurtosis and skewness. In this work, 9 textural features were extracted from the co-occurrence matrix. Several features can be extracted from GLCM [24, 25].



(a)



(b)

Figure 8. (a) Check of recognized status for normal area, (b) The results of selection

About 19 characteristics have been independently derived from both kurtosis and skewness function extraction methods. Therefore, for the classification stage, 46 features were used for each image.

4.2 KNN Classification

KNN classification was done to detect benign/malignant calcifications as selected by the user [19]. KNN model was trained on 8 images (some of which had dense and some had glandular tissue). Figure 9 shows the names of the training images. It was tested on fatty tissue images and gave excellent results on detection as well as classification.

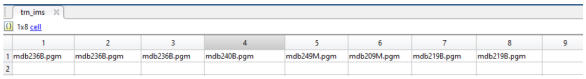


Figure 9. The names of the training images

5 Conclusion

Since microcalcifications are small and standardized in scale and shape, auto mammographic image analysis is a challenge for even skilled radiologists. Poor mammogram contrast and high breast tissue density that can obscure the essential characteristics of MCs.

In this work, an algorithm was developed to help doctors scan for breast cancer by using fuzzy histogram equalization and Otsu's process for detecting MCs and diagnosis of breast cancer. The enhancement algorithm greatly developed the context contrast of MCs and thus improved the recognition of MCs. The algorithm applied also proves that KNN give excellent results on detection as well as classification.

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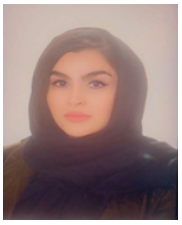

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