Detection of Micro-Calcifications in Mammograms using Optical Scanning Holography

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Abstract

This paper proposes a novel approach for processing digital mammograms to detect micro-calcifications. They may be so small that they are almost undetectable visually, but it could be indicators of a possible malignancy. An analysis algorithm based on optical holographic property of images and clustering principles are proposed to detect the micro-calcifications. This process consists of three stages. In the first stage the mammographic patterns are subjected to optical holographic analysis. The resulting images are passed to the second stage, in which morphological operations are performed. The third stage detects the malignant portions of the mammographic pattern using unsupervised texture classification by extracting laws features. Texture classification is an important image processing task with a broad application range. Many different techniques for texture classification have been explored. This paper explores the unsupervised classifications of digital mammograms using K-means and Fuzzy C-means approaches. Results show that the proposed techniques detect the malignant portions of the breast very well thus enabling earlier detection of tumor.

Keywords: *mammogram, texture classification, optical hologram, FCM, image processing*

1. Introduction

Breast cancer is the most frequent cancer disease, and a leading cause of cancer death among women. Worldwide survey reports are found alarming. The survival rate is greatly influenced by how early the cancer is detected and treated. Mammograms are X-ray projections of the breast tissue onto a detector array or a film plate. The exposure of the mammographic film or detector array is a function of the intensity of the electromagnetic waves transmitted through the breast. Most of the western countries today have mammographic screening programs. A screening is defined as the presumptive identification of unrecognized disease or defect by application of tests, examinations, or other procedures. In some western countries every women between 50 and 69 years of age are invited to screening every second year. Evaluating the screening data is a time demanding process and also requires the involvement of labour. Cancer is only found in a small percentage of the cases, and due to the vast amount of images relatively rapid interpretation is done. Hence, there is a risk that subtle abnormalities can be overlooked. Although the presence of micro-calcifications in a mammogram is well-known to be a sure indicator of possible malignancies, their detection relies on the experience and visual capacity of the radiologist. So ,even for the most widely experienced radiologists, the likelihood of detecting zones of the mammogram as being worthy of further attention known as regions-of-interest (ROI) which is dependent on human visual capacity. The result is that if these regions are very small, they will certainly go unnoticed. Fortunately, the levels of detail that are now attained in digital mammograms can show ROIs that are minuscule in size. The problem is being able to identify them as such a capacity known as “sensitivity”. The other aspect that one must bear in mind is what is known as “sensibility” [3-6]. This refers to the selectivity that any lesion-detecting system must have in order not to consider significant regions of the mammogram that really has no medical significance, such as “artifacts”, fatty tissue, etc. In this article, it was proposed to be an unsupervised classification approach that could very well detect the malignant portions of the breast thus enabling earlier detection of tumor.

2. Motivation

The motivation of this research was due to the fact that the early detection is curable. Screening mammography is performed on patients with no signs of breast cancer and we believed that these mammograms have no sign of clear abnormality and would be much the same pattern. The image processing technology is becoming accurate and advanced capable of producing a good result on analyzing two images. Early detection was identified and would reduce the breast cancer cases and death.

3. Methodology

It was proposed a novel approach to computer-aided diagnosis of breast cancer using mammographic findings. This is illustrated using the architecture shown in Figure.1.

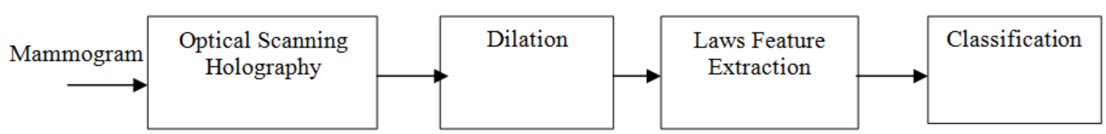

Figure 1. Proposed Approach

3.1. Optical Scanning Holography and Reconstruction

The Optical Screening holography (OSH) is a novel technique, was first suggested by Poon and Korpel in 1979 [7], in which holographic information of an object can be recorded using heterodyne optical scanning. Corresponding to the principle of holography, the technique also consists of two stages: the recording or coding stage, and the reconstruction or decoding stage. The Experimental setup is given in Figure.2. In the recording stage, the 3-D object is 2-D scanned by a time-dependent Fresnel zone plate (TDFZP) [18]. The 3-D FZP is created by the superposition of a plane wave and a spherical wave of different temporal frequencies. The spherical wave of different temporal frequency was generated by AOM (Acousto-optic modulator). In this paper, 2D Sine FZP hologram of the mammogram image was generated using time dependent Fresnel zone plate. While the mammogram image was scanned, a photo detector collected the light transmitted through the image and delivered a heterodyne scanned current corresponding to micro-calcification i_Ω(x,y), as an output [8-17]. The current, which contains the FZP coded information of the mammogram image, was then mixed up to become a demodulated signal, i_d *(x*, y). When the demodulated signal was synchronized with the *x* and y scans of the *x* - y optical scanning system and fed to a 2-D display, what was displayed (or stored in a computer) in 2-D was a hologram or a FZP coded information of the mammogram being scanned. To decode the information or to reconstruct the mammogram image, the 2-D display was illuminated by the laser light. To demodulate and extract the in-phase component i_Ω(x,y) which was mixed with cos(Ωt) and low pass filtered the demodulation process. Since an electronic processing technique was used in the context of holographic technique, the process was real time, bypassing the use of films for recording. Such holographic technique is commonly known as electronic holography.

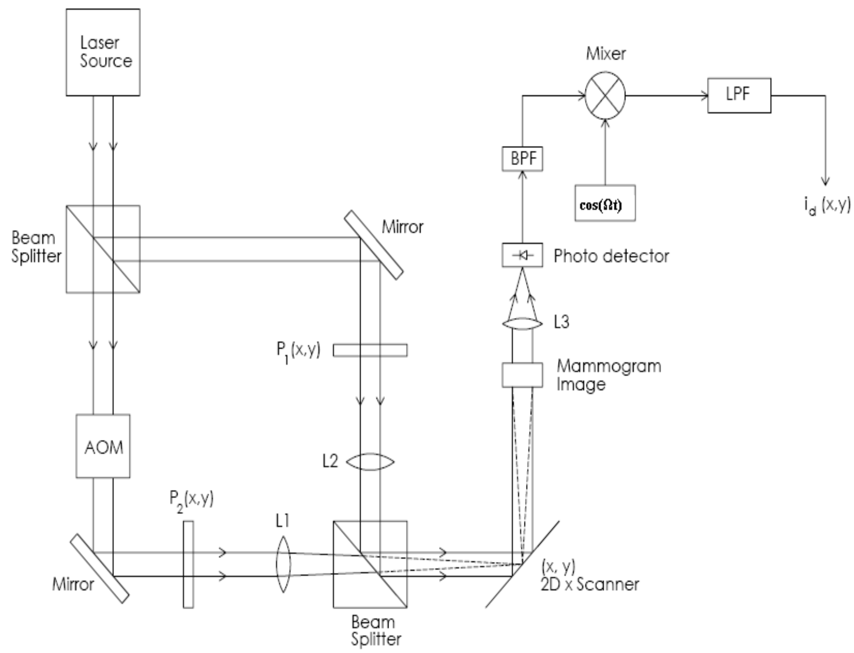

Figure 2. Experimental Setup used for Holographic Recording by OSH

In our system we had chosen two pupils such as $p_1(x,y) = p_2(x,y) = \delta(x,y)$ and with this choice of the pupils, the OTF that is (Optical transfer function) of the optical scanning system is,

$$OTF_\Omega\left(k_x, k_y; z\right) = \exp\left[-j\frac{z}{2k_o}\left(k_x^{\;2} + k_y^{\;2}\right)\right] \qquad (1)$$

$$= OTF_{osh}\left(k_x, k_y; z\right) \qquad (2)$$

Where the subscript OSH denotes that the particular achieved OTF was for holographic recording. The recorded image was a two dimensional hologram of the mammogram image *t(x,y) (*which is the demodulated signal i_d *(x ,* y)) the equation for hologram is given by

$$t(x, y) = Re[\int F^{-1}\{F\{|\Gamma_o(x, y; z)|^2\}OTF_{osh}\left(k_x, k_y; z\right)\}dz \qquad (3)$$

$$= Re[\int F^{-1}\{F\{|\Gamma_o(x, y; z)|^2\} \exp\left[-j\frac{z}{2k_o}\left(k_x^{\;2} + k_y^{\;2}\right)\right]\}dz \qquad (4)$$

From the above equation, it was clear that holographic recording process in the frequency domain can be interpreted as the object spectrum along its depth (z) was processed by the ***OTF*** of the form given by equation 1. To clearly see why this corresponds to holographic recording, the equation was rewritten in terms of convolution and it was

$$t(x,y) = Re[\int |\Gamma_o|^2 * h(x,y:z)dz] \qquad (5)$$

It can be written in terms of free space impulse response *h(x, y; z)*

$$h(x,y,z) = \frac{jk_o}{2\pi z}\exp\left[-j\frac{k_o}{2z}(x^2+y^2)\right] \qquad (6)$$

$$t_{sin}(x,y) = Re[\int h(x,y:z) \otimes |\Gamma_o|^2 dz \qquad (7)$$

$$= \int \frac{k_o}{2\pi z}\sin\left[\frac{k_o}{2z}(x^2+y^2)\right] \otimes |\Gamma_o|^2 dz \qquad (8)$$

Since $|\Gamma_o|^2$ represents the intensity distribution which was strictly positive, the re-operation was distributed to the function of h. The 'sin' in the left side of the calculation denoted a sine function involved in the calculation of the integral.

$$|\Gamma_o|^2 = \delta(x-x_o)^2 + (y-y_o)^2 \qquad (9)$$

$$t_{sin} \sim \left\{\frac{k_o}{2z}\left[(x-x_o)^2+(y-y_o)^2\right]\right\} \qquad (10)$$

This was the hologram of the offset delta function. Hence in optical scanning holography 3D holography can be thought of as a 2D transverse correlation between the real part of the free space impulse response and the 3D object planar intensity distribution at z. The resulting correlation was then integrated along the depth of the object to obtain the hologram of the whole 3D object. To put into a wider the ***Re*** operation can be replaced by ***Im*** operation.

$$t_{cos}(x,y) = Im[\int h(x,y:z) \otimes |\Gamma_o(x,y,;z)|^2 dz \qquad (11)$$

$$= \int \frac{k_o}{2\pi z}\cos\left[\frac{k_o}{2z}(x^2+y^2)\right] \otimes |\Gamma_o(x,y;z)|^2 dz \qquad (12)$$

For $|\Gamma_o|^2 = \delta(x-x_o)^2 + (y-y_o)^2$ we call $t_{sin}(x,y)$ as sine- Fresnel zone plate (sine-FZP) hologram and $t_{cos}(x,y)$ as cosine–FZP hologram of the object. Then the holographic information was available in electronic form. In our proposed method, Sine FZP hologram of the mammogram image was used. This optically processed hologram image was further processed for segmenting the tiny calcium deposits called micro-calcification. Detection of micro-calcification using cosine FZP hologram is our future work.

3.2. Dilation

The dilation of image t(x,y) with an structuring element B was calculated as

$$t(x,y) \oplus B \qquad (13)$$

The dilation would result in a 3-D surface, which contained all the points with a distance to the upper side of the original surface [20]. Executing this process on an image of object thickens the outlines.

3.3. Laws Features Extraction

The word texture is in general regarded as surface appearance or tactile qualities. A texture can be regarded as a self-similar object. In image processing the texture of a region describes the pattern of spatial variation of gray tones (or in the different colour bands in a colour image) in a neighborhood that was small compared to the region. By definition, texture classification was to identify the texture class in a region, whereas texture segmentation means finding a boundary map between different textures regions of an image. There was an ambiguity here since classification can be used for segmentation. The term texture classification in the following was used, though the goal of the classification was segmentation. Most texture classification algorithms start by finding a local feature vector which in turn was used for classification. Texture classification using learned (over complete) dictionaries and sparse representation was a relatively new area in texture classification.

The texture energy measures developed by Kenneth Ivan Laws at the University of Southern California have been used for our application [21]. These measures were computed by first applying small convolution kernels to a digital image, and then performing a nonlinear windowing operation.

The 2-D convolution kernels typically used for texture discrimination were generated from the following set of one-dimensional convolution kernels of length five:

L5 = [1 4 6 4 1]

E5 = [-1 -2 0 2 1]

S5 = [-1 0 2 0 -1]

W5 = [-1 2 0 -2 1]

R5 = [1 -4 6 -4 1]

These mnemonics stand for Level, Edge, Spot, Wave, and Ripple. All kernels except L5 were zero-sum. From these one-dimensional convolution kernels, 25 different two-dimensional convolution kernels were generated by convolving a vertical 1-D kernel with a horizontal 1-D kernel. As an example, the L5E5 kernel was found by convolving a vertical L5 kernel with a horizontal E5 kernel. Of the 25 two-dimensional convolution kernels that could be generated from the one-dimensional kernels above, and 24 of them were zero-sum; the L5L5 kernel was not. A listing of all 5x5 kernel names were,

L5L5 E5L5 S5L5 W5L5 R5L5

L5E5 E5E5 S5E5 W5E5 R5E5

L5S5 E5S5 S5S5 W5S5 R5S5

L5W5 E5W5 S5W5 W5W5 R5W5

L5R5 E5R5 S5R5 W5R5 R5R5

Following steps were applied to form a set of texture energy measures for each pixel in optically processed mammogram image.

Step I: Applying Convolution Kernels

Each of our 25 convolution kernels were applied to optically processed mammogram image. The result was a set of 25 NxM grayscale images of optically processed mammogram image. This would form the basis for our textural analysis.

Step II: Performing Windowing Operation

Every pixel in this 25 NxM separate grayscale images were replaced with a Texture Energy Measure (TEM) at the pixel. It was done by looking in a local neighborhood (using a 15x15 square) around each pixels and summing together the absolute values of the neighborhood pixels. A new set of images were generated, which would be referred as the TEM images, during this stage of image processing. The following non-linear filter was applied to each of this 25 NxM images.

$$NEW(x,y) = \sum_{i=-7}^{7} \sum_{j=-7}^{7} \left| OLD(x+i, y+j) \right| \tag{14}$$

At this point, it was generated 25 TEM images from the optically processed mammogram image. These images were denoted by the names of the original convolution kernels with an appended ``T" to indicate that this was a texture energy measure (i.e. the non-linear filtering was performed). These TEM images were named as,

L5L5T E5L5T S5L5T W5L5T R5L5T

L5E5T E5E5T S5E5T W5E5T R5E5T

L5S5T E5S5T S5S5T W5S5T R5S5T

L5W5T E5W5T S5W5T W5W5T R5W5T

L5R5T E5R5T S5R5T W5R5T R5R5T

Step III: Normalizing Features for Contrast

All convolution kernels used thus far were zero-mean with the exception of the L5L5 kernel. In accordance with Laws' suggestions, it was used for normalization of the image; normalizing any TEM image pixel-by-pixel with the L5L5T image would normalize that feature for contrast. The L5L5T image was typically discarded and a data set was obtained, where every pixel was represented by 25 texture features.

3.4 Classification

The following two methods of classification were employed for the segmentation of Micro-Calcification from the mammogram images.

3.4.1 K-Means Clustering: The K- means algorithm [22], which is a crisp clustering algorithm, partitions a collection of n vector x_j, j = 1,…, n into C groups G, i = 1,…,c, and found a cluster center in each group such that a cost function (or an objection function) of dissimilarity (or distance) measure was minimized. When the Euclidean distance was chosen as the dissimilarity measure between a vector x_k in group j and the corresponding cluster center c_i, the cost function could be defined by

$$J = \sum_{t=1}^{c} J_t = \sum_{t=1}^{c} \left(\sum_{k, x_k \in G_t} \| x_k - c_t \|^2 \right) \tag{15}$$

where

$$J_t = \sum_{k, x_k \in G_t} \| x_k - c_t \|^2 \tag{16}$$

was the cost function within group i. Thus, the value of Ji depends on the geometrical properties of G_i and the location of c_i. A generic distance function d(x,c) was applied for vector x_k in group I and the overall cost function was written as

$$J = \sum_{t=1}^{c} J_t = \sum_{t=1}^{c} \left(\sum_{k, x_k \in G_t} d(x_k - c_t) \right) \tag{17}$$

For simplification, the Euclidean distance was used as the dissimilarity measure and the overall cost function was expressed in equation (17). The partitioned groups were typically defined by a c x n binary membership matrix U, where element U_{ij} was 1 if j^{th} data point x_j belongs to group i, and 0 otherwise. Once the cluster centers c_i were fixed, the minimizing U_{ij} for the equation (16) was modified as,

$$U_{ij} = \begin{cases} 1 & \text{if } \| x_j - c_i \|^2 \le \| x_j - c_k \|^2, \text{ foreachk} \ne i, \\ 0 & \text{Otherwise} \end{cases} \tag{18}$$

The equation (18) stated that x_j belonged to group i, if c_i was the closest center among all centers. Since a data point could only be in a group, the membership matrix U had the properties as,

$$\sum_{t=1}^{c} U_{ij} = 1, \forall_j = 1, \ldots, n \tag{19}$$

and

$$\sum_{i=1}^{c} \sum_{j=1}^{n} U_{ij} = n \tag{20}$$

if U_{ij} was fixed, then the optimal center c_i that minimize the equation (15) was the mean of all vectors in group i.

For a batch mode operation, the K-means algorithm was presented with a data set x_i, i = 1,…,n and the algorithm determined the cluster center c_i and the membership matrix U iteratively using the following steps:

Step 1*:* Initialize the cluster center c_i,.i = 1,…,c. This was typically achieved by randomly selecting c points from the data points.

Step 2*:* Determine the membership matrix U using equation (18)

Step 3: Compute the cost function (or objection function) using equation (15). Stop, if either it was below a certain tolerance value or its improvement over previous iteration was below a certain threshold.

Step 4: Update the cluster center. Go to step 2.

3.4.2 Fuzzy C-Means clustering: Fuzzy C-Means clustering (FCM) [22], also known as ISODATA, is a data clustering algorithm in which each data point belongs to a cluster to a degree specified by a membership grade. FCM and its derivatives had been used very successfully in our application, for segmentation of Micro-Calcification in mammogram images. FCM partitions a collection of n vector xi, i= 1,…,n into c fuzzy groups, and found a cluster center in each group such that a cost function of dissimilarity measure was minimized. FCM employed fuzzy partitioning such that a given data point may belong to several groups with the degree of belongingness specified by membership grades between 0 and 1. To accommodate the introduction of fuzzy partitioning, the membership matrix U was allowed to have elements with values between 0 and 1. Imposing normalization stipulated that the summation of degrees of belongingness for a dataset always be equal to unity.

$$\sum_{t=1}^{c} U_{ij} = 1, \forall_j = 1, \ldots, n \tag{21}$$

The cost function (or objective function) for FCM was,

$$J(U, c_1, \ldots. c_c) = \sum_{t=1}^{c} J_t = \sum_{j=1}^{c} U_{ij}^m d_{ij}^2 \tag{22}$$

where U_{ij} was between 0 and 1;c_i was the cluster center of fuzzy group i; $d_{ij} = \|c_i - x_j\|$ was the Euclidean distance between ith cluster center and jth data point and m ε (1,∞) was a weighting exponent. The necessary conditions for the above equation to reach a minimum could be found by forming a new objective function J as,

$$\begin{aligned} J(U, c_1, \ldots, c_c . \lambda_1, \ldots . \lambda_n) &= J(U, c_1, \ldots\ldots, c_c) + \sum_{j=1}^{n} \lambda_j \left(\sum_{i=1}^{n} U_{ij} - 1 \right) \\ &= \sum_{i=1}^{c} \sum_{j}^{n} U_{ij}^m d_{ij}^2 + \sum_{j=1}^{n} \lambda_j \left(\sum_{i=1}^{c} U_{ij} - 1 \right) \end{aligned} \tag{23}$$

where λ_j, j = 1 to n, were the Lagrange multipliers for the n constraints in membership matrix. By differentiating J (U, $c_1 \ldots c_c$, $\lambda_1 \ldots \lambda_n$ to all its inputs arguments, the necessary conditions for cost function to reach its minimum were

$$c_t = \frac{\sum_{j=1}^{n} U_{ij}^m x_j}{\sum_{j=1}^{n} U_{ij}^m} \tag{24}$$

and

$$U_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{xj}} \right)^{2/(m-1)}} \tag{25}$$

The fuzzy C- means algorithm was simply an iterated procedure through the preceding two conditions.

In a batch-mode operation, FCM determined the cluster centers ci and the membership matrix U using the following steps:

Step 1: Initializing the membership matrix U with random values between 0 and 1 such that the constraints were satisfied.

Step 2: Calculating c fuzzy cluster center by equation (21).

Step 3: Computing the cost function (or objection function) by equation (22). Stop if either it was below a certain tolerance value or its improvement over previous iteration was below a certain threshold.

Step 4: Computing a new U by (25). Go to step 2.

4. Calcification of Soft Tissue Lesions/Masses in Mammograms and Performance Evaluation

All experiments in this chapter were performed on digitized mammograms from the MIAS database provided by the Mammographic Image Analysis Society (MIAS) in the UK [24]. The images from this database have a resolution of 50 microns (0.05 mm/pixel), 8 bits per pixel. The proposed method segmented /classified the input mammogram into suspicious and non-suspicious regions (i.e. normal breast tissue and malignant tissues). Our aim was that no case of malignancy-indicating micro-calcification should escape radiological analysis. Therefore it was started with two basic assumptions: (i) the micro-calcifications had an aspect that differentiates them from the other elements of the breast because of their different X-ray opacity; and (ii) micro-calcifications that were in an incipient stage, and they involved a very small proportion of the total area of the breast because they otherwise would be clearly visible to any radiologist and there would consequently be no point in using this proposed system.

The process of detection was performed in three stages. First the X-Ray mammograms patterns were subjected to optical holographic analysis. The resulting image was passed through the second stage in which the morphological process of thickening known as dilation using a structuring element was performed as a preprocessing before classification. The processed image was then passed to the next stage in which the micro-calcifications of the suspicious regions were classified by extracting the texture features using Law's texture approach. The unsupervised classification based on Fuzzy C-means and K-means were performed. The K-means algorithm, was a crisp clustering algorithm which partitioned a collection of n vector $\mathbf{x}_j$, $j = 1,\ldots,n$ into c groups G_i, $i= 1,\ldots,c$, and found a cluster center in each group so that the objective function of dissimilarity measure was minimized. Fuzzy C-Means clustering also known as ISODATA was a data clustering algorithm in which each data point belonged to a cluster to a degree specified by a membership grade.

The detection results for various mammogram patterns using K means clustering algorithm and fuzzy C means clustering algorithm were illustrated in Figures (3-5).The regions in a mammogram corresponding to tumor tissues had different texture patterns and gray levels than the normal ones, so that it was possible to classify these regions.

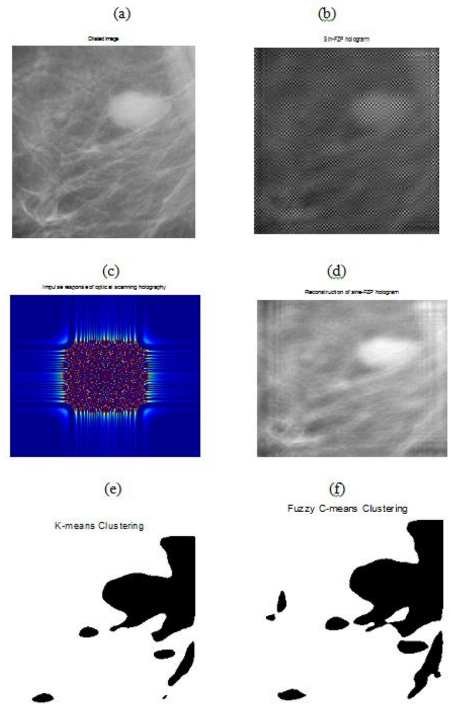

Figure 3. (a) Morphological Mammogram; (b) Optical Sine Hologram; (c) Impulse Response of Mammogram with Sine Hologram; (d) Reconstructed Optical Sine Hologram; (e) K-means Segmentation; (f) Fuzzy C-means Segmentation

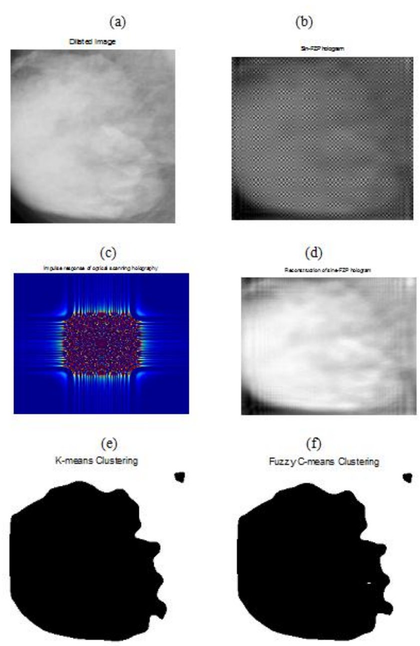

Figure 4. (a) Morphological Mammogram; (b) Optical Sine Hologram; (c) Impulse Response of mammogram with sine hologram; (d) Reconstructed Optical Sine Hologram; (e) K-means Segmentation; (f) Fuzzy C-means Segmentation

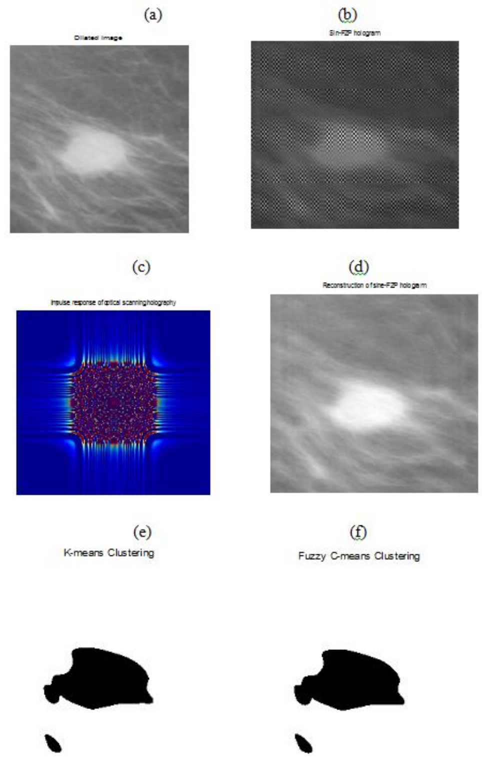

Figure 5. (a) Morphological Mammogram; (b) Optical Sine Hologram; (c) Impulse Response of Mammogram with Sine Hologram; (d) Reconstructed Optical Sine Hologram; (e) K-means Segmentation; (f) Fuzzy C-means Segmentation

Figures 3-5 shows the segmented region obtained after processing the input image by the proposed optical holographic based segmentation. Comparing with the actual mammogram image and the image reconstructed after optical processing, the brightness level of tiny deposits was increased. The proposed scheme was therefore used to capture only regions of interest in mammograms, thus eliminating undesired information. The interest areas in mammograms consisted of high density regions, represented by light shades of gray and white. It was known that most abnormalities, including masses, micro-calcifications and lesions occur in regions of high density.

5. Conclusion

We have presented a novel approach to the problem of computer-aided analysis of digital mammograms for breast cancer detection. The algorithm developed here classifies mammograms into normal and abnormal. The structures in mammograms produced by normal glandular tissue of varying density were processed first, i.e., holographic information of the image was recorded using heterodyne optical scanning. Then the linear markings formed by the normal connective tissue were identified and removed using morphological operation termed dilation. Any abnormality presented in the mammogram was therefore enhanced in the residual image, which made the decision regarding the normality of the mammogram much easier. The Texture Laws features were extracted and classification approaches using K-means and Fuzzy C-means showed good classification results. Using the mammographic data from the

Mammographic Image Analysis Society (MIAS) database a recognition score of 82% and 86% were achieved using K-means and Fuzzy C-means approaches respectively. So this proposed approach is recommended highly for the detection of micro-calcification.

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