FEATURE LEVEL FUSION OF INFORMATION FROM MAMMOGRAM AND ULTRASOUND IMAGES FOR DETECTION OF MICRO- CALCIFICATION IN BREAST

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Abstract: Breast cancer is the most common, life-threatening cancer in women. Detection of Microcalcification plays a crucial role in diagnosis of breast cancer. Different medical modalities like mammogram, ultrasound, MRI, etc. are used in all phases of cancer detection, which provide morphological, metabolic and functional information of tissues. By integrating this extracted information from multimodalities in a meaningful way assists in clinical decision making. Proposed work helps in classification of breast microcalcification as benign or malignant for early detection of breast cancer using mammograms and Ultrasound modalities. This approach is based on the fusion of information from two modalities at feature level. Discriminative statistical, spatial and texture features of malignant microcalcifications in mammograms and ultrasound are extracted and fused. SVM classifiers are used to classify malignant microcalcifications which achieved 91.3% sensitivity.

Keywords: Microcalcification, Mammogram, Ultrasound, Fusion, Dualmodality

I. INTRODUCTION

Breast cancer is the most common, life-threatening cancer which has been reported to have the highest mortality rates of any women's cancer. It is the second leading cause of cancer deaths among women in United States and it is the leading cause of cancer deaths among women in the 40 – 55 age groups. Approximately 182,000 new cases of breast cancer are diagnosed and 46,000 women die of breast cancer each year in the United States. In 2009, about 40,610 women died from breast cancer in the United States [1, 2].

Microcalcifications(MC) are tiny calcium spots found in women's breast as women gets older. These are too small, bright white spots and most of the time they are found to be harmless. But when they are seen in clusters or all in line it is a sign of cancer. Two main types of calcifications are: Macrocalcifications which are large and almost round in shape on mammograms. These are usually not related to cancer. Microcalcifications are small and appear in clusters which may be benign or malignant. They vary in size from 0.1mm to 5mm in diameter thus radiologists find very difficult to analyse. Major criteria's that are considered to analyse individual calcifications are size, shape, number, distribution and its radiographic density. Ducal carcinoma in situ (DCIS) is most frequently found breast cancer which can be detected before the invasion stage and are found in clusters of microcalcification. It is very difficult to detect the calcifications even they are in clusters, but the survival depends on how early the cancer is detected. So, any MC formation should be detected at the benign stage. Thus Computer Aided Diagnosis is used to detect MC clusters [3].

Mammogram is a modality which can read some signs of abnormalities like shape, asymmetry area and clusters in microcalcifications [4]. MC's appear as clusters, patterns, nodular points with brightness and small granular points in breast tissue. But normal mammary ducts and vessels appear to be linear in structure. Detection of these clusters in mammograms is still a challenge due to dense breast tissue which makes suspicious areas invisible [5]. Although X-ray mammogram detection is best way of screening the breast cancer, breast ultrasound is more popular because of its non-invasiveness and low cost [6].

Ultrasound is most commonly known as reliable modality for detection of cyst or breast lesions. But the advances and refinement in US equipment has made it more applicable even for detecting and characterizing small lesions and also microcalcifications. MC's are brighter reflectors than the surrounding breast parenchyma without an acoustic shadow in sonography. Literature says that in a study of 89 tumors found in 84 patients, micro-calcifications were visible in 44 breast cancers using high resolution ultrasound. A study also says that high resolution ultrasound has detected MC in 6 cases that were found negative in mammogram. High resolution ultrasound has shown 95% sensitivity and 87% so it is a sensitive and reliable diagnosis modality for micro-calcification presented within a mass lesion [7]. Microcalcifications within masses are more visible in ultrasound because solid nodules provide great echogenicity. Thus malignant MC's are more visible in ultrasound than benign calcifications.

Mammography and ultrasonography are currently the most sensitive noninvasive modalities for detecting breast cancer but they have their own limitations. This justifies that information retrieved from one modality are not sufficient to analyze the abnormalities of breast cancer in early stages. Integrating the information from different modalities in different phases is widely used for generating more diagnostic and clinical values in medical imaging. But it needs proper fusion techniques and modalities to be employed [9]. Hence this paper proposes a new methodology to extract features from dual modalities (ultrasound and mammogram) and to fuse them to improve the performance of detection and classification of microcalcifications in breast. Multimodal techniques supply complementary information for improved therapy planning. As early detection of cancer is probably the major contributor to a reduction in mortality for certain cancers, guided and targeted minimally invasive therapy has the promise to improve the outcome and reduce collateral effects [2,9].

II. REVIEW OF RELATED WORKS

State of art on detection of microcalcification in mammograms, ultrasound, multi modality and feature level fusion appear in our literature. C.C. Diaz [10] has proposed evaluation four different algorithms based on morphology to detect microcalcifications in mammographic images. A morphological algorithm based on contrast enhancement operator followed by extended maxima thresholding was used to retrieve the features of microcalcifications. Work also states that SVM with Gaussian kernel was the most suitable for detecting micro-calcifications. Sensitivity obtained was 84% for glandular; 87% for dense tissue; 88.7% for fatty breast. Saranya and Bharathi [11] have worked with detection of MC in mammograms using image enhancing techniques.

Pouya Derakhshan [12] used wavelets to detect breast calcifications in mammograms. According to their study Wavelet theory provides a powerful framework for multiresolution analysis and it can be used for texture analysis also. Marcelo de Almeida Duarte [13] proposed Otsu's method and morphological filters for Segmenting mammographic microcalcifications. Canny edge detection is also applied to identify microcalcifications contour candidates for each region-of-interest (ROI). They assed their method on 1000 ROIs from 158 digital images and even considered the radiologists opinion. The rates of ROIs adequately segmented were 97.8% for one radiologist and 97.3% for the other. Ebrahim Jelvehfard [14] presented a study on MC detection in mamographic images using 2D wavelet coefficients histogram. In that paper CAD system was presented for microcalcification detection in mammography images. The system acheived accuracy of 93.80% and precision of 94.55%. 2-D wavelet transform was used in feature extraction step and to classify these features, SVM was employed.

Yufeng Zhou [8] has compared the performance of ultrasound with mammography and MRI. On summary, although digital image processing techniques aided the automated cancer detection and enhanced the outcome. The superiority of mammography over ultrasound has been shown in a variety of clinical studies but in the detection and diagnosis of benign lesion and during the distinction between cystic and solid masses, ultrasound is the best choice. Shafiul Islam [15] has proposed methodology for detecting point Microcalcifications in Breast. Main aim of their work was to improve the capability of ultrasound images for detecting breast MC's and remove the major barriers of ultrasound for early breast cancer detection.

Han-ling and Fan [19] has presented a hybrid optimization algorithm to deal with multimodal (CT and MRI) medical images. They used mutual information as a similarity measure and proved that subvoxel accuracy can be achieved for an efficient image registration and can avoid getting into local optimum. Andrzej Krol and Ioana [20] proposed an approach for co-registration of PET images with MR images in image fusion level. They proved that it is an alternative to surgical breast biopsy.

Francis and Thomas [21] investigated on fusion of data from mammography, ultrasound and non invasive infrared imaging modalities to improve early diagnosis. They concluded that data fusion will add early back into early detection of breast cancer. Survey of literature summarizes that there is scope for research in fusing the information from multimodalities. Thus in our proposed methodology we are introducing a new approach of fusing features from mammograms and ultrasound to detect microcalcifications in order to improve the diagnosis by giving second opinion to the radiologist that hopefully reduce the rate of biopsy.

III. DATASET AND METHODOLOGY

Initially to work with mammograms data was data were obtained from the mini-MIAS which consisted of 322 digitized mammography images owned by the UK National Breast Screening Programme. Mini-MIAS was obtained by rescaling MIAS images from 50 to 200 microns pixel size, and consisted of images of 1024 _ 1024 pixels with 8 bits per pixel (0 corresponded to black, and 255 corresponded to white). Mini-MIAS give the diagnosis for each mammogram, where 23 images correspond to micro-calcifications (benign or malign). It even gives the information about coordinates (x, y) at the center of abnormality either in cluster or isolated micro-calcifications and the value of radius (in pixels) of a circle that involves microcalcification. But further for our work with Ultrasound we created our own dataset. For the work carried out on fusion we have collected data of Ultrasound and mammogram images of same person. Data set was created by collecting ground truth marked images from expert radiologists. Images with single calcification and cluster of microcalcifications were collected. For each image, a rectangular region of interest (ROI) including microcalcification and the area around it were determined by an experienced radiologist.

Mammograms are normally a best choice for screening women who are less than 40 years. But due to dense breast in younger women detection of abnormalities is not easy. Ultrasound is a commonly used diagnostic too but it is not approved by FDA (Food and Drug Administration) for screening. In this paper we propose a work to demonstrate the fusion of features from these two modalities mammograms and ultrasound. Figure 1. Shows the overall methodology followed in our work.

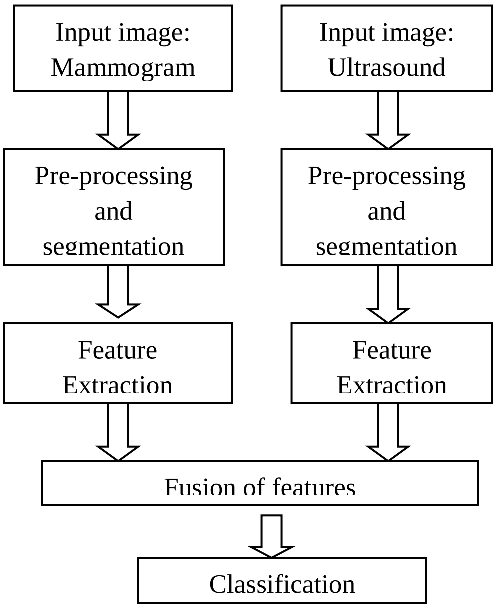

Fig 1. Proposed methodology.

A. Preprocessing and segmentation of mammograms*:*

Preprocessing images of mammograms is a process to reduce the work area so that we will be left with only breast area eliminating background and other isolated regions. This phase helps to improve the quality of image and assists in getting accurate results. Initially, using logarithmic enhancement method overall image is significantly enhanced to improve the visibility of the regions near the boundary and to sharpen the edges of boundary. Image is then binarized using threshold value to separate the breast region from background.

Segmentation of microcalcification in a mammographic image I was carried out by considering the image as set of points arranged in matrix form of size m x n. Whole image I was split into n different sub regions which intern produces sub-images of size n x n which showed the information about the existence of microcalcifications. Histogram of gray level was constructed for each of these sub-images and mean gray level was calculated to interpolate. Image after interpolation represented local background image I_{Bk}. Image I_{Bk} was then subtracted from original image I. Thresholding was done using both local and global thresholding. Image after segmentation highlighted microcalcifications so that features related to microcalcifications can be easily extracted and false positives can be minimized.

B. Feature extraction (Mammogram)*:*

In mammograms we have extrcted features related to microcalcification. Microcalcifications are very important finding for the early detection of breast cancer. To detect such microcalcifications we have extrcted features in different domains such as Spatial and Textural.

- **Spatial features:**

Microcalcifications are related to local maxima (LM) value in the image. An important spatial feature may be the correlation between this LM and its neighboring pixels. Assuming that there can be more than one cluster of calcification we aim in viewing them from different branches. Because if we find a local maxima in one direction try to look in a different direction it may not be local maxima. Thus we find standard deviation at different branches which provides solution for above problem. For this, we have taken the size of ROI as 128 x 128 and the window (block) size as 17 x 17.

Point P in Figure 2. is a LM which can be viewed from all directions. While calculating LM at one branch we need to know counter value and threshold value. When we find threshold between central pixel and neighbouring pixel if standard deviation is greater than the threshold value we increment the counter. Thus actual LM is the point which has a counter value as 8.

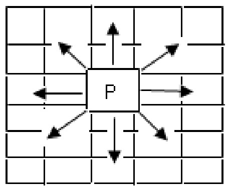

Fig 2: Standard Deviation at different points

Point P in Figure 2. is a LM which can be viewed from all directions. While calculating LM at one branch we need to know counter value and threshold value. When we find threshold between central pixel and neighbouring pixel if standard deviation is greater than the threshold value we increment the counter. Thus actual LM is the point which has a counter value as 8.

At point P(x,y):

$$SD_i = \sqrt{\sum_{i=1}^{n}(C - x_i)^2} \qquad i= 1,2,\ldots\ldots 8 \quad \rightarrow \quad (1)$$

Where SD_i is a standard deviation at i th branch, C is the center of cluster, x_i is value of gray level at some position i and n is number of pixels.

Along with standard deviation for each block of X x Y we also find some other spatial features like: average pixel intensity, and average energy of each pixel intensity which are defined as follows:

$$Avg = \frac{1}{X\,x\,Y}\sum_{m=1}^{X}\sum_{n=1}^{Y} f(m,n) \rightarrow (2)$$

$$AvgE = \frac{1}{X\,x\,Y}\sum_{m=1}^{X}\sum_{n=1}^{Y}(f(m,n))^2 \rightarrow (3)$$

We also consider varience of pixel intensity VPI and energy varience EV as follows:

$$VPI = \sum_{m=1}^{X}\sum_{n=1}^{Y}(f(m,n) - Avg)^2 \rightarrow (4)$$

$$EV = \sum_{m=1}^{X}\sum_{n=1}^{Y}(f(m,n) - AvgE)^2 \rightarrow (5)$$

- **Texture features :**

The word texture is means the appearance of surface or tactile qualities of image. A texture can also 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 color bands in a color image) in a neighborhood that is small compared to the region [5]. Gabor filters are proven to be best for extracting texture properties in image. Most important properties like translation, rotation, scale, illumination and invariance can be extracted. Two dimensional Gabor function g(x,y) and its Fourier transform G(u,v) is given as:

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right) exp\left[-\frac{1}{2}\left(\frac{x'^2}{\sigma_x{}^2} + \frac{y'^2}{\sigma_y{}^2}\right) + 2\pi j w_x\right] \rightarrow (6)$$

$$G(u,v) = exp\left[-\frac{1}{2}\left(\frac{(u-W)}{\sigma_u{}^2} + \frac{v^2}{\sigma_v{}^2}\right)\right] \rightarrow (7)$$

Where $\sigma_u = \frac{1}{2\pi\sigma_x}$ and $\sigma_v = \frac{1}{2\pi\sigma_y}$ gabor functions will form a non-orthogonal set.

Other Texture features are intensity based features and Gray Level Co-occurrence Matrix (GLCM) based features. Intensity based features depend on individual pixel value. Variations in intensity can be measured using features like mean and standard deviation. GLCM is also a method used to analyze image texture. It considers the relation between 2 pixels (reference pixel and neighbor pixel) at a time [22]. Texture features extracted from GLCM are as follows:

Mean: Mammograms containing microcalcifications have higher mean value where, mean is a average intensity value of mammographic image given as:

$$\mu = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} P(i,j) \rightarrow (8)$$

Standard deviation: This gives dispersion of values in image around mean .

$$SD = \sqrt{\mu^2} \rightarrow (9)$$

Energy: Energy provides orderliness of image.

$$E = \sum_{i,j=0}^{n-1} P(i,j)^2 \rightarrow (10)$$

Correlation: This helps in measuring joint probability occurrence of specified pixel pairs.

$$Cor = \sum_{i,j=0}^{n-1}\frac{(ixj)P(i,j) - \mu_i\mu_j}{\sigma_i\sigma_j} \rightarrow (11)$$

Contrast: Distinguishes the object from its background.

$$C = \sum_{i,j=0}^{n-1}(i-j)^2\, P(i,j) \rightarrow (12)$$

The features that are extracted from mammograms are not sufficient for classification, thus some other characteristic features are extracted from ultrasound images to detect and classify microcalcifications.

C. Preprocessing and segmentation of Ultrasound:

Ultrasound is a popular breast diagnosis modality from decades. As these images are of low contrast, preprocessing helps in noise reduction and contrast enhancement. In this paper we have used median filters to preprocess ultrasound images. Median filters are very effective in removing noise by preserving edges. This filter works by sliding a window on image pixel by pixel and replacing each value with a median value of neighboring pixels [16]. Normally breast ultrasound images have non-uniform background thus we have used adaptive contrast enhancement method to enhance the image before segmentation.

Segmentation is a method which partitions image into distinct regions and helps in extracting region of interest (ROI). We have applied Watershed Segmentation method to extract the microcalcification part from the breast region. This method classifies pixels into regions using gradient descent on image features and analysing the weak points along region boundaries. Using suitable mapping image feature space is treated. Watershed method uses analogy of water which gradually fills low lying landscape basins because of which it is called watershed algorithm. The size of the basins grows with increasing amounts of water until they spill into one another. Small basins (regions) gradually merge together into larger basins. Regions are formed by using local geometric structure to associate the image domain features with local extremes measurement [16]

D. Feature Extraction (Ultrasound):

Feature refers to a piece of information that has relevance in solving the computational tasks related to a certain application. Feature extraction means quantitative measurement or analysis of images. To detect and classify abnormalities like microcalcifications in ultrasound images we extract different statistical features like: mean, standard deviation and variance. To improve the classification we also extract some texture features from ultrasound images. Texture features that discriminate microcalcification from normal regions are: contrast, energy and entropy. Where Entropy and Inverse difference is given by

Entropy S= $\sum\sum p(x,y)\log p(x,y) \rightarrow (13)$

E. Feature level Fusion of mammogram and ultrasound images:

The features retrieved from mammogram and ultrasound is dissimilar in terms of dimension. For fusion of features we needed coherent dataset from both modalities which belong to a same person. Data set was created by collecting and getting the ground truth marked images from expert radiologists trained with those kinds of images. The fusion process fuses this collection of features into a single feature set. Feature level fusion is a medium level fusion strategy which performs well, if the features are homogenous. If the features are heterogeneous, then it requires normalization to convert them into a range that makes them more similar. We have used Z-score normalization which transforms the scores to a distribution with mean of '0' and standard deviation of '1'.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

Our method is applied on 25 set of images where in each set we had one mammogram and one ultrasound image of same person. Feature level fusion concatenates the features from mammogram and ultrasound. This concatenated feature vector will have a better discrimination than individual feature vectors. Feature level fusion needs proper normalization to address the difference in measurement scale because, during fusion we augment features that are retrieved from different extraction methods. One more problem associated with this fusion scheme is we need to use same classifier to the fused feature set. But the feature sets from mammogram and ultrasound may have different utilities and may have their own individuality favored classifiers.

Support vector machines (SVM) are a learning tool based on modern statistical learning method that classifies binary classes. SVM has been shown to perform better than many other classification algorithms due to several reasons. In our proposed method we have used SVM classifiers to classify the fused feature vector. The sensitivity achieved by SVM classifier in classifying breast microcalcifications using dual modality is 91.3%. Whereas, sensitivity achieved in classifying breast microcalcifications using single modality mammogram and ultrasound was 89.5% and 85.7% respectively

CONCLUSION

Information from different modalities provide additional information for classification and improves classification rate. Fusion is carried out in feature level by extracting discriminative features from mammograms and ultrasound. Spatial and textural features are extracted from mammographic images. Statistical and textural features are extracted from ultrasound images and these features were fused. When we compare the results of fusion with individual modalities we can conclude that multimodal results show better performance in classifying breast microcalcifications.

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