DETECTING MICRO-CALCIFICATION CLUSTERS IN MAMMOGRAMS USING CONTOURLET AND PCNN

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ABSTRACT

According to World Health Organization (WHO), breast cancer is most common cancer in woman in worldwide, becoming to one of the most fatal form of cancer. The mammography analysis is an effective technology for early detection of breast cancer. MC (Micro-calcification clusters) is a major part of breast cancer so detection of MC plays an important role in computer aided system (CAD) so to improve the MC detection rate in mammograms. The proposed method comprises the three main steps. Firstly, remove label and pectoral muscle which adopting the largest connected region marking and region growing method, and enhance MCs using the combination of double top-hat transform and grayscale adjustment function, secondly, remove noise and other interference information, and retain the significant information by modifying the contour-let coefficients using nonlinear function and lastly we use the non-linking simplified pulse-coupled neural network to detect MCs. : In our work, we choose 118 mammograms including 38 mammograms with micro-calcification clusters and 80 mammograms without micro-calcification to demonstrate our algorithm separately from two open and common database including the MIAS and JSMIT; and we achieve the higher specificity of 94.7%, sensitivity of 96.3%, AUC of 97.0%, accuracy of 95.8%, MCC of 90.4%, MCC-PS of 61.3% and CEI of 53.5%, these promising results clearly demonstrate that the proposed approach outperforms the current state-of-the-art algorithms.

Keywords/ Index Term — Mammography Micro-calcification clusters (MCs) detection Contourlet transform Simplified pulse-coupled neural network (SPCNN)

1. INTRODUCTION

Breast cancer has become an increasing problem for woman in world-wide according to International Agency for Research on Cancer (IJRC) 2012, there were estimated nearly 1.7 million people diagnosed with breast cancer on a global scale, which was close to 11.9% of all cancers s, and about 0.52million women died of the disease in the same year. The new cancer cases will increase to nearly 19.3 million by 2025, and it is showing that breast cancer is the fastest growing of all diseases. To improve the diagnosis and prognosis of breast cancer, early detection is becoming more and more important. The early detection technique is widely used by radiologist and it can detect 85-90% of all breast cancer. The MCs provide the size, shape, texture and distribution of the micro-calcification, so the accurate detection of MCs is a critical step in computer aided system (CAD).

For automatic detection of MCs, which give assistance to radiologists in diagnosis of breast cancer. The MCs detection in CAD system has sustained for decades but the research of calcification detection still possess meaningful and challenging topic because of inhomogeneous background and high noise level in mammography. As per studies these methods divided into classic methods and emerging methods. These classic methods can be decomposed into three steps; firstly, reduce the noise and enhance MCs; secondly, detect the MCs applying a specific segmentation technique; thirdly, select true MCs by diverse novel methods. A variety of techniques have been used in different steps. For mammogram enhancement, variety attempts have been done, such as improved histogram equalization [4], image enhancement based on wavelet fusion [5], automated lesion intensity enhance [6], modified multi-fractal analysis [7], etc.; in the segmentation step, many techniques have been suggested, such as multi stable cellular neural networks, geodesic active contours (GAC) technique associated with anisotropic texture filtering [4], case-adaptive decision rule method [5], new scale-specific blob detection technique [2], etc.; in the third step, select true MCs by extracting a group of features of micro-calcifications like moment-based geometrical features [7], wavelet feature and Gabor feature [9] and so on but the the hybrid detection algorithms combining different theories seems more popular.

For years, Oliver et al. [3] presented a knowledge-based approach to detect MCs automatically, which was based on local features extracted by a bank of filters to gain a local descriptor of the micro-calcifications morphology, the approach was demonstrated on the full digitized MIAS database and full-field digital mammograms extracted from a non-public database, and resulted in better than 80% sensitivity at 1 false positive cluster per image. s. In their approach, the position of the MCs was taken into account, so the system could locate the calcified regions quite accurately. They used 7 abnormal and 1 normal mammogram images from MIAS digital mammogram database to design the system. Lifeng [5] introduced a novel multi-scale and multi-position classification (MSPC) method for detecting mammographic MCs, and their experiments tested on the digital database for screening mammography (DDSM) data showed that the detection rate of clustered pleomorphic calcification (CPMC) could reach up to 97.26% with a 36.84% false positive rate. Yu and Huang [6] investigated the performance of MCs by adopting combined model-based and statistical textural features, 20 mammograms containing 25 areas of MCs from the MIAS database were used to test the performance, and a true positive rate of about 94% was achieved at the rate of 1.0 false positive per image, or the false positives per image could be reduced to 0.65 false positive per image at the rate of true positive about 90%

Its employing multi-statistical filters and wavelet transform, the proposed method was found sensitive in detecting MCs in mammogram images by achieving a high true positive percentage of 98.1% and a low false positive rate 0.63 cluster per image for both MIAS and USF database design the system. Lifeng [5] introduced a novel multi-scale and multi-position classification (MSPC) method for detecting mammographic MCs, and their experiments tested on the digital database for screening mammography (DDSM) data showed that the detection rate of clustered pleomorphic calcification (CPMC) could reach up to 97.26% with a 36.84% false positive rate. Zhang and Gao [9] presented an innovative framework for detection of MCs in mammograms employing the twin support vector machine (TWSVM), the proposed scheme is evaluated on the DDSM database results, there was still room for improving MCs detection rate. In our work, a new MCs detection method is proposed, in the first step, remove label and pectoral muscle adopting the largest connected region marking and region growing method; then enhance MCs using the double top-hat transform and grayscale-adjustment function; in the second step, obtain the suspicious calcification clusters by reconstructing the modified sub bands only with high frequencies contour-let transform coefficients; finally, use the non-linking SPCNN to detect calcification clusters.

2. Literature Survey

For years, Oliver et al. [3] presented a knowledge-based approach to detect MCs automatically, which was based on local features extracted by a bank of filters to gain a local descriptor of the micro-calcifications morphology, the approach was demonstrated on the full digitized MIAS database and full-field digital mammograms extracted from a non-public database, and resulted in better than 80% sensitivity at 1 false positive cluster per image. . Pal et al. [4] proposed to use multi-layered perceptron network to segment the MCs. In their approach, the position of the MCs was taken into account, so the system could locate the calcified regions quite accurately. They used 7 abnormal and 1 normal mammogram images from MIAS digital mammogram database to design the system.

Lifeng [5] introduced a novel multi-scale and multi-position classification (MSPC) method for detecting mammographic MCs, and their experiments tested on the digital database for screening mammography (DDSM) data showed that the detection rate of clustered pleomorphic calcification (CPMC) could reach up to 97.26% with a 36.84% false positive rate. Malar et al. [7] exhibited the effectiveness of wavelet based tissue texture analysis for detecting MCs in mammograms using extreme learning machine (ELM), the sample image were collected from the MIAS database, and achieved relatively better classification accuracy (94%).

AbuBaker [8] proposed a novel algorithm to detect and classify the MCs accurately and automatically by employing multi-statistical filters and wavelet transform, the proposed method was found sensitive in detecting MCs in mammogram images by achieving a high true positive percentage of 98.1% and a low false positive rate 0.63 cluster per image for both MIAS and USF database.

In our work, a new MCs detection method is proposed, in the first step, remove label and pectoral muscle adopting the largest connected region marking and region growing method; then enhance MCs using the double top-hat transform and grayscale-adjustment function; in the second step, obtain the suspicious calcification clusters by reconstructing the modified sub bands only with high frequencies contour-let transform coefficients; finally, use the non-linking SPCNN to detect calcification clusters. The results show our method is efficient and accurate. Lifeng [5] introduced a novel multi-scale and multi-position classification (MSPC) method for detecting mammographic MCs, and their experiments tested on the digital database for screening mammography (DDSM) data showed that the detection rate of clustered pleomorphic calcification (CPMC) could reach up to 97.26% with a 36.84% false positive rate.

Chen et al. [2] presented a multi-scale topological approach to MCs classification by building a multi-scale graph of the inter-micro-calcification relationships, then various graph metrics were extracted from this graph and were fed into a k-nearest neighbor classifier to produce the final classification results, and evaluated this method on MIAS database.

3. Proposed System

3.1 Image Preprocessing

The Mammogram includes breast region, pectoral muscle, background and label. In order to reduce the interference and improve the detection accuracy, we use the maximum connected region marking and region growing method to remove label and pectoral muscle. In image enhancement is to improve the subjective image quality, and make the enhanced image is more suitable for a specific c application. Here we propose a hybrid method which combines double top-hat transform with a “ball-shaped” non-flat structuring element [4], and grayscale-adjustment function to enhance MCs. The double top-hat transform with a “ball-shaped” non-flat structuring element only enhance the MCs and retain the original features of mammogram simultaneously. The implementation is shown as follows:

$$r_{TH} = I_O - r_B \qquad (1)$$

Where $r_{TH}r_{TH}$ is used to define the difference between the original image $I_O I_O$ and $r_B r_B$. $r_B r_B$ is grayscale opening with the structuring element SE.

$$\emptyset_{TH} = \emptyset_B - I_O \qquad (2)$$

Where $\emptyset_{TH}\emptyset_{TH}$ is defined as the difference between the grayscale closing $\emptyset_B\emptyset_B$ using the structuring element SE, and the original image $I_O I_O$.

In our work, we choose the 3D structuring elements, nonflat SE, which is used to explore the intensity "shape" of features in the image. For example, the non-flat "ball-shaped" structuring element with R = 8, H = 50 is shown. we evaluate the enhancement results using enhancement measure (EME) [26], entropy parameters, and PSNR (peak signal to noise ratio) [4]. These parameters are computed for all 23 images. The EME and entropy values of original image are given, the improvement in the EME and entropy notifies that our enhancement method have better performance. PSNR is a measure of the deviation of the enhanced image from the original image with respect to the peak value of the gray level. Higher PSNR value denotes more light intensity free from image.

For MCs image, we apply double top-hat transform by the non-flat "ball-shaped" structuring element with R = 8, H = 50, and then use the gray scale-adjustment function to improve the visual perception, the grayscale-adjustment function used in this work is the gamma function, as are shown as follows:

$$Y_1 = r - \min(r) \tag{3}$$

$$Y_2 = \frac{Y_1}{\max(Y_1)} \tag{4}$$

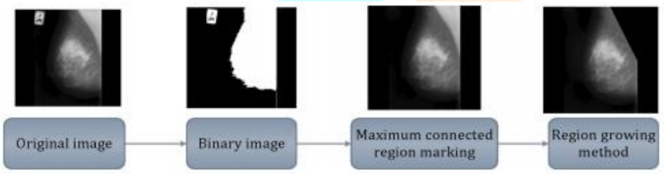

Fig. 1.1 Removing label and Pectoral muscle.

3.2. The Contourlet transform

Contourlet transform (CT) is proposed by Do and Vetterli [7], which has better performance of representing edges and textures of images than wavelets for its anisotropy and directionality, and is well-suited for multi-scale image enhancement. It is constructed by Laplacian pyramid (LP) and directional filter banks (DFB), which firstly uses the LP to capture singular points in the horizontal and vertical directions, and then use DFB link singularity into linear structure It can capture the intrinsic geometrical structure of original image.

It is an excellent tool for the analysis of 2D digital images, and it has been used in mammogram images. In our work, we adopt simple nonlinear function to modify the contourlet coefficients to further enhance MCs, and remove noise and other interference information, retain the significant information and obtain suspicious calcification area, the effect is particularly obvious.

3.3. Micro-calcification clusters detection

The non-linking simplified pulse-coupled neural network (SPCNN) is used to detect micro-calcification, then post processing is utilized to remove the isolated points, finally we get the micro-calcification clusters. Pulse coupled neural network (PCNN) is a single layer neural network, which is stemmed from the Eckhorn's neuron model [30]. The Eckhorn's neuron model was provoked by the observations of synchronous pulse bursts in the cat visual cortex. PCNN is different with the traditional neural networks, and has been proven to be highly effective in a diverse set of applications. It has done well in image segmentation because of its biological background, and it is usually applied to binary image segmentation.

Clearly, although PCNN model can effectively simulate the synchronous firing phenomenon, it is uneasy to use and spend too much time because of too many parameters. Therefore, some simplified models are proposed to solve the practical problems. Chen et al. [3] proposed the SPCNN model derived from SCM. SPCNN model is employed in our work, and according to the characteristic of MCs, we introduce the non-linking SPCNN model as follows :

$$F_{ij} = S_{ij} \tag{5}$$

$$U_{ij}[n] = e^{-aF} U_{ij}[n-1] + S_{ij} \tag{6}$$

$$Y_{ij}[n] = \begin{cases} 1 & if\ U_{ij}[n] > E_{ij[n-1]} \\ 0 & otherwise \end{cases} \quad (7)$$

$$E_{ij}[n] = e^{-a^E} E_{ij}[n-1] + V_E Y_{ij}[n-1] \quad (8)$$

The pixels with similar gray value may be fired at the same time, which present the effect of the coupled SPCNN model. Although the non-linking SPCNN reveals the effect of the coupled SPCNN model, we should note that the coupling is decided by the mathematical properties of differential equations, and do not fully reflect the interaction between neurons, here we call the coupling characteristics of PCNN as coupling characteristics of mathematics. It can be seen that the non-linking PCNN has simple structure and lower computational complexity.

4. Assessment measures

In order to show the effectiveness of the proposed method, we test it on two common and open database. The first dataset is taken from the MIAS database, we choose 23 mammograms (7 Glandular, 10 Dense, 6 Fatty) containing micro-calcification clusters and 50 mammograms (15 Glandular, 20 Dense, 15 Fatty) without micro-calcification randomly, In order to preserve complete geometric information of the mammograms, we apply the whole image to the proposed method rather than the region of interest Because that MIAS database provides the central coordinate and radius definitively, and the second dataset just draw out the rough location, we make the following definitions to further explain the performance of the proposed method respectively.

For the first database, we draw a bounding circle to the detected MCs, and make the following definitions [35]: (1) If more than 2/3 bounding circle of the micro-calcification clusters are overlapped with the criterion region of ground truth segmented by experts, we consider it as correct, that is true-positive (TP), otherwise is considered wrong, namely false negative (FN). (2) For mammograms that contain multiple calcification clusters area, if we detect at least one satisfy (1), we define it as TP. (3) For mammograms without micro-calcifications, if we cannot detect out any micro-calcifications, we consider it as true negative (TN), otherwise it is false positive (FP).

For the second database, the expert just draw out the rough location, so we adopt the visual perceptual evaluation [36], we choose 20 people randomly and stand in line to review the images independently, the reading time of each observer was limited to less than 20 s for each reading

(1) We provide the maximum score of 10 points, and let each observer grade the left image comparing to the right image, we record the 20 sets of data and get the average, if the average score is more than 8, we considered itto be correct, that is TP, otherwise is considered wrong, namely FN. (2) For mammograms without calcification, if we cannot detect out any calcification, we consider it is TN, otherwise it is FP

According to the definitions above, for the sake of make further assessment, we statistics the entire overlapping ratio for 23 mammograms with micro-calcification clusters in MIAS database, and also we record the results of the visual perceptual evaluation of 15 mammograms with micro-calcification clusters in the second database.

Sensitivity is used to deal only with positive cases; it presents the proportion of the detected positive cases over the actual positive cases, the higher the sensitivity, the lower false negative rate.

$$sensitivity = \frac{TP}{TP + FN}(\%) \quad (9)$$

Specificity is used to deal only with negative cases; it reflects the proportion of the detected negative cases over the actual negative cases, the higher the specificity, the lower false positive rate.

$$specificity = \frac{TN}{TN + FP}(\%) \quad (10)$$

Accuracy can be used to deal with all cases; it indicates the precision of predict results. The higher accuracy, the better system is.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}(\%) \quad (11)$$

Higher sensitivity and specificity can lead to higher accuracy. But in clinical practice, sensitivity and specificity, we cannot have both. If we increase the sensitivity of diagnosis, necessarily reduce its diagnostic specificity, so we need to make a compromise according to our demanding.

At last, we define a comprehensive evaluation indicator (CEI) by using sensitivity, specificity, accuracy, MCC and PS, we define CEI as follows:

$$CEI = \frac{Sensitivity * Specificity * Accuracy * MCC}{1 + PS} (\%) \quad (12)$$

The receiver operating characteristic (ROC) curve is used to measure the predictive accuracy of the proposed model. It indicates the true positive rate and false positive rate. The AUC is a descriptor of test result. If the AUC is close to 1.0 indicates that the diagnostic test is reliable; on the contrary, AUC is close to 0.5 demonstrates the unreliable test result. But the disadvantage is that the different sample proportion may change the area under the ROC, so it is not the best evaluation indicator.

4.1 Subjective evaluation

The 'mdb209', 'mdb213' and 'mdb252' have one MCs areas, the 'mdb249' has two micro-calcification areas, and we can detect them precisely we guess different type of the breast and the different database may have an impact on the algorithm, hence we choose three different types in MIAS and two different databases to test the effect; in the last, we compare our method to the current state-of-the art algorithms. Objective evaluation is done by using PS, sensitivity, specificity, AUC, accuracy, MCC, MCC PS and CEI.

4.2 Objective evaluation

Taking notice of the fact that the types of breast make a difference to the method, our method has better detection result to fatty tissue, the MCC PS and CEI can give a comprehensive evaluation. The glandular and dense breasts have high density fiber and dense tissue, which have an impact on algorithm to detect the calcification clusters. The good choice of the sample proportion is helpful to the fatty breasts.

The sensitivity, accuracy and MCC value in MIAS is a bit larger than the second database except specificity. So just apply these evaluation measures cannot reflect the difference of different databases, so here we mainly apply the MCC PS and CEI to evaluate the result. Noticing that the MCC PS and CEI value in MIAS database are higher than the second database; the MCC PS value is 2.1% higher in MIAS than the second database, and the CEI value is 2.9% higher, which reveals that the performance in MIAS is better than the second database

To further fully confirm the effectiveness of our method, we compare our method to three referenced methods [6] based on MIAS database in recent years But there are some weaknesses in their technique, the proposed method failed on low density mammogram images and micro-calcifications neighboring the pectoral muscle.

presented an improved multi-scale morphological gradient watershed segmentation (Improved-MMGW) method for automatic detection of cluster micro-calcification, the true positive rate is observed to be 0.953 and 0.94 for MIAS and NMR datasets respectively, which better than O-MMGW by approximately 20%, but the method was sensitive to highlighted portion on the boundaries of mammography It can be seen that when considering sensitivity, specificity, accuracy, AUC and MCC to evaluate the algorithm, our method performs Table 9 – Evaluation indicator for different methods. Evaluation indicator Ref. [6] Ref. [38] Ref. [39] Our method TP 36 143 37 22 FN 4 7 3 1 TN 46 43 40 48 FP 14 7 0 2 PS 66.7 300.0 100.0 46.0 Sensitivity (%) 90.9 95.3 100.0 95.7 Specificity (%) 52.2 86.0 92.5 96.0 AUC (%) 76.9 92.8 96.9 97.2 Accuracy (%) 82.0 93.0 96.25 95.9 MCC (%) 65.3 81.3 92.8 90.7 MCC PS (%) 39.2 20.3 46.4 62.1 CEI (%) 15.2 15.5 41.3 54.7 Database MIAS relatively better than the other approaches;

The CEI embraces sensitivity, specificity, accuracy, MCC and PS value to give the method a comprehensive evaluation, which is more believable.

4. Conclusion

In this method, they use CT and non-linking SPCNN to detect micro calcification clusters but in preprocessing to remove label and pectoral muscle, so after that we take combination of double top-hat transform and grayscale adjustment to enhance micro-calcifications. We use non-linking SPCNN to detect calcifications clusters. We employ CT to deal with image, which capture the information of calcification because of the anisotropic, multi-scale and multi-direction properties of the CT. it is simple and fast and obtain high detection rate so we first come up with evaluate indicators that take the proportion of samples into account the algorithm performance comprehensively, which is the highlights of this work.

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