Physics Based Contrast Marking and Inpainting Based Local Texture Comparison for Clustered Microcalcification Detection

Xin Yuan^{1,2} and Pengcheng Shi²

¹ College of Computer Science

Zhejiang University, Hangzhou, China

² Department of Electrical and Electronic Engineering

Hong Kong University of Science and Technology

Clear Water Bay, Kowloon, Hong Kong

{eeyxy, eeship}@ust.hk

Abstract. As important early signs of breast cancers, microcalcifications (MCs) are still very difficult to be reliably detected by either radiologists or computer-aided diagnosis systems. In general, global, regional, and local properties of the mammogram should all be considered in the analysis process. In our effort, we incorporate the physical nature of the imaging process with the image analysis techniques to detect the clustered microcalcifications based on local contrast marking and self-repaired texture comparison. Suspicious areas are first obtained from a simplified X-ray imaging model where the MC contrast is a nonlinear function of local intensity. Following a removal and repair (R&R) procedure of the suspicious areas from their surrounding background textures, pre- and post- R&R local characteristic features of these areas are extracted and compared. A modified AdaBoost algorithm is then used to train the classifier for detecting individual microcalcification, followed by a clustering process to obtain the clustered MCs. Experiments on the MIAS database have shown promising results.

1 Introduction

In many parts of the world, breast cancer remains the leading cause of death for women. The most effective technique for early detection is screening mammography, followed by diagnostic mammography if necessary, a low-dose x-ray procedure that can detect tiny tumors and breast abnormalities. Microcalcifications (MCs) are the earliest signs of breast cancer [2], appearing as tiny (0.05–1mm in diameter) bright spots embedded within non-stationary backgrounds [4]. MC detection has been so far an extremely difficult task because of the projection nature of mammogram, the low image contrast in high tissue density regions, the varying shapes of the MC clusters, the blurred margins of the MCs, and the different types of noises caused by the x-ray imaging and digitization processes.

A typical MC detection algorithm can be divided into three steps: the enhancement of mammographic features, the localization of suspicious areas, and

the classification of these areas [7]. Treating the microcalcifications as high frequency signals, various multi-scale filtering techniques have been widely used in recent studies of suspicious area localization [3,13,14]. Although these methods have shown some effectiveness in MC detection, they often miss significant numbers of microcalcifications in high tissue density regions and produce false positives caused by interferences from normal breast tissues, blood vessels, and fat. Effort thus has been devoted to employ local signal-dependent thresholds which take into account background intensity information [16]. Once the suspicious regions are localized, texture features are extracted from these areas, and various training and classification techniques have been used [5,8,20].

Without prior knowledge on imaging parameters, we believe that the detection of suspicious areas must incorporate imaging-physics knowledge. Because the MC contrast is a nonlinear function of its local image intensity, as previously shown that intensity contrast of a MC of a given size increase then decrease as its surrounding background intensity increases [17], a *particle analysis* (PA) scheme, which regards image as a series of scan lines consisting of several peak-valley intervals, is developed to mark suspicious pixels from background¹. Corresponding suspicious areas, or *blobs*, are then formed through morphological operations.

Further, we hypothesize that the *local* characteristic features of the tissues surrounding microcalcifications are of particularly great importance for MC detection, and it motivates us to make *direct* texture comparison between a suspicious area and its localized neighborhood through a texture removal and repair (R&R) process. The so-called *virtual biopsy* (VB) procedure, which aims to extract unbiased, classifiable features from the suspicious areas, removes the blobs to form empty holes and then fills them up with texture inpainting techniques. Local characteristic features of these blobs can then be extracted and compared before and after the R&R process. A modified AdaBoost algorithm is used to classify the feature space into normal and abnormal categories, where blobs belonging to the abnormal category are regarded as individual MCs. A clustering process is finally performed to obtain the clustered MCs.

2 Methodology

In this paper, we are focusing on our contributions in terms of physics-based marking of the suspicious pixels and recognition of the individual microcalcifications using localized texture comparison.

¹ We have recently noticed that in [18], mammogram intensity is plotted as a function of the pixel location in 2D, and flagpole-like blobs are detected within a given local range. For computational considerations, we have independently developed the 1D particle analysis along 4 scan lines instead of the 2D analysis. For all our experiments sofar, we have not missed any suspicious MCs using the 1D analysis.

Fig. 1. A intensity scanline (left), the corresponding particle analysis curve (middle, slightly enlarged), and the feature distribution and nonlinear threshold function (right).

2.1 Physics-Based Marking of Suspicious Pixels: Particle Analysis

It has been observed from mammographic images that pixel contrast is an important sign in discriminating suspicious pixels from background tissues. Further, we notice that, typically, the MC contrast in darker area is actually larger than that in brighter area. This inspires us to think that the lower bound of MC contrast could be a function of background intensity, i.e. $I_c = f(I_b)$. Limited by the available space, readers are referred to [19] for detailed analysis of the *much simplified* physical nature of the mammographic imaging process.

To effectively detect the suspicious MC pixel from mammogram, we use the profiles of the multi-orientation (horizontal, vertical, diagonal, and anti-diagonal) image scanlines to obtain the particle contrast, which is evaluated as the minimum of two difference values from peak to the left and right valleys. A particle consists of pixels within an interval that contains a peak I_{peak} and is bounded by two nearest valleys I_{left} and I_{right} . The particle contrast is then $I_c = \min(I_{peak} - I_{left}, I_{peak} - I_{right})$ and the particle intensity is $I_b = \max(I_{left}, I_{right})$. Fig. 1 shows a scanline and the associated particle contrast analysis diagram.

After marking all MC particles of the training images, feature vectors $\mathbf{V}_p = (I_c, I_b, s)$ are formed where $s = +1$ if p is a microcalcification and $s = -1$ if p is normal. The nonlinear threshold function $I_{th} = f(I_b)$ is obtained through a training process, which is posed as an optimization problem on an empirical risk function, $R(I_c, I_b, s) = \sum_{i=1}^l \theta[1 - s_i(I_{ci} - f(I_{bi}))]$ with l the number of samples, to maximize the number of positive samples, minimize the number of false positive samples, and maximize the margin between the nearest positive and negative samples. Detailed algorithm can be found in [19]. The right figure of Fig. 1 shows the feature distribution of the training set, as well as the obtained nonlinear threshold function.

Once the suspicious pixels are marked, a region growing procedure is used to obtain the blobs. The blobs are discarded if their size is larger than $W_m \times W_m$ with W_m the maximum width of microcalcification, 1mm in our implementation.

2.2 Recognition of Individual Calcification: Virtual Biopsy

Blob Removal and Repair. Assuming that normal tissues have continuous texture properties, then mislabeled normal blobs can be *recovered* from their surrounding tissues. If we remove a blob from the mammogram and use texture inpainting techniques to *repair* the void, we can get direct measure on the difference between the blob and its surrounding tissues. If the blob is a true MC, then it would not be reasonably recovered by its surrounding normal tissues, and the pre- and post- R&R difference would be substantially different from the cases where the blob is actually normal tissue.

Since the breast tissues have relatively high local variations, typical inpainting techniques based on total variation [6] or texture [11] cannot obtain the desirable results in our experience. Instead, we have developed a new texture-like inpainting approach based on wavelet diffusion. Since the variation of the image intensity reflects the changes of tissue types and thickness, we regard these signals as the linear combination of some basis functions. The texture-like inpainting now becomes a diffusion process of these basis functions. Because wavelet theory is well suited to analyze local scale phenomena [12], we use the diffusion of the wavelet subbands to realize our texture-like inpainting.

In our implementation, an image is decomposed into four subbands (smoothing, horizontal, vertical, and diagonal), denoted by W_{LL} , W_{HL} , W_{LH} , and W_{HH} , which represent responses of different orientations. With I_i , ($1 \leq i \leq N$), denoting the neighboring subblocks of blob I which is being repaired, and $d(I_i, I)$ denoting the distance between I_i and I , we use the following weighted average of subbands to estimate the blob's wavelet subbands, and reconstruct the inpainted blob $I_{inpaint}$ by inverse wavelet transform:

$$\begin{aligned} W_{LL}(x, y) &= \frac{1}{C} \sum_{i=1}^N e^{-d(I_i, I)} W_{LL}^i(x, y), \quad W_{HL}(x, y) = \frac{1}{C} \sum_{i=1}^N e^{-d(I_i, I)} W_{HL}^i(x, y) \\ W_{LH}(x, y) &= \frac{1}{C} \sum_{i=1}^N e^{-d(I_i, I)} W_{LH}^i(x, y), \quad W_{HH}(x, y) = \frac{1}{C} \sum_{i=1}^N e^{-d(I_i, I)} W_{HH}^i(x, y) \end{aligned}$$

and $C = \sum_{i=1}^N e^{-d(I_i, I)}$. The advantage of this inpainting scheme is that, in theory, local structure can be *recovered* after repairing. Visual appearance of the repaired voids is actually not important here, because we only care for the blob's texture features extracted from pre- and post-inpainting process. Hence, the appearance continuity between the blob and its background is not necessary achieved. Nevertheless, visually plausible inpainting results are often obtained and an example is shown in Fig. 2.

Local Feature Extraction. The following local features from the pre- (I) and post-repairing ($I_{inpaint}$) blob are extracted:

- M_S : the post-inpainting mean intensity of the *support domain* of the blob, which includes the blob and its surrounding subblocks I_i ;

Fig. 2. Effectiveness of image inpainting: pre-inpainting (left), blob removal (middle), and post-inpainting (right).

- S_I : area of the blob;
- N_s : number of suspicious blobs within the support domain of blob I ;
- post-inpainting average energies of the detailed subbands of the blob support domain, which reflect texture information of the support domain:

$$E_{HL} = \frac{1}{M_{HL} \times N_{HL}} \sum_{i=1}^{M_{HL}} \sum_{j=1}^{N_{HL}} |W_{HL}(i, j)|,$$

$$E_{LH} = \frac{1}{M_{LH} \times N_{LH}} \sum_{i=1}^{M_{LH}} \sum_{j=1}^{N_{LH}} |W_{LH}(i, j)|$$

$$E_{HH} = \frac{1}{M_{HH} \times N_{HH}} \sum_{i=1}^{M_{HH}} \sum_{j=1}^{N_{HH}} |W_{HH}(i, j)|$$

where M_{HL} , M_{LH} , and M_{HH} are widths, N_{HL} , N_{LH} and N_{HH} are heights of the wavelet subbands, and W_{HL} , W_{LH} and W_{HH} are wavelet coefficients;

- ΔM_s : difference between the pre- and post-inpainting mean intensity values of the blob support domain;
- $\Delta \sigma_s$: difference between the pre- and post-inpainting intensity standard deviations of the blob support domain;
- ΔV_{max} : difference between the pre- and post-inpainting maximum intensity values of the blob support domain;
- ΔE_{HL} , ΔE_{LH} , and ΔE_{HH} : differences between the pre- and post-inpainting average energies of the detailed subbands of the blob support domain.

We note that these particular features, in one way or another, have actually been used in many earlier efforts. We do want to point out that the *localized comparison* of these features is, as far as we know, the completely novel idea.

Training and Classification. In the training step, we have adopted and modified the AdaBoosting algorithm [9,15], which boosts a series of weak classifiers into a strong classifier. The rationale is that the AdaBoosting allows a certain

number of false positives for each classifier, thus conceptually handles the overlapping feature distributions between the normal and microcalcification tissues.

Given l training samples $(\mathbf{x}_1, s_1), (\mathbf{x}_2, s_2), \dots, (\mathbf{x}_l, s_l)$, $\mathbf{x}_i \in \mathbf{X}$ where $\mathbf{X}$ is a N -dimensional feature space, $s_i \in \mathbf{S} = \{-1, +1\}$ where $\mathbf{S}$ are labels for positive and negative samples, and weights C^+ and C^- :

1. Let $t = 1$, initialize:

$$\omega_i^{(1)} = \begin{cases} \frac{C^+}{C^+ + C^-} \cdot \frac{1}{m^+} & \text{if } s_i = +1 \\ \frac{C^-}{C^+ + C^-} \cdot \frac{1}{m^-} & \text{if } s_i = -1 \end{cases}$$

$$i = 1, 2, \dots, l$$

where m^+ and m^- are the numbers of positive and negative samples, with $m^+ + m^- = l$;

2. Train a weak classifier $h_t(\mathbf{x}) = \text{sign}(x_t - h_t)$ using distribution $\omega_i^{(t)}$, i.e. minimize $R_{emp}(\mathbf{x}) = -\sum_{i=1}^l \omega_i^{(t)} s_i h_t(\mathbf{x}_i)$, where x_t is an element of the feature vector, and h_t is a threshold value of the element decided by this step;
3. Calculate the training error $\epsilon_t = \sum_{h_t(\mathbf{x}_i) \neq s_i} \omega_i^{(t)}$;
4. Choose $\alpha_t = \frac{1}{2} \ln \frac{1-\epsilon_t}{\epsilon_t}$;
5. Update $\omega_i^{t+1} = \omega_i^t e^{[-\alpha_t s_i h_t(\mathbf{x}_i)]}$, $i = 1, 2, \dots, l$;
6. Normalize $\omega_i^{t+1} = \frac{\omega_i^{t+1}}{\sum_{i=1}^l \omega_i^{t+1}}$, $i = 1, 2, \dots, l$;
7. Let $t = t + 1$, if $t < T$ where T is the maximum number of weak classifiers, goto step 2; otherwise, stop.

Hence, the final decision function becomes:

$$H(\mathbf{x}) = \text{sign} \left[\sum_{t=1}^T \alpha_t h_t(\mathbf{x}) \right] \quad (1)$$

We have used a simple threshold function as the weak classifier for each dimension of the feature space, with $T = N$ and $h_i(\mathbf{x}) = \text{sign}(x_i - h_i)$, and where x_i is one element of the feature vector and h_i is a threshold value of the corresponding element.

2.3 Clustering of Microcalcifications

Clustered MCs, which is typically defined to have at least 2 to 3 MCs within a 1cm^2 region [10], provide useful diagnosis information. We have used a simple clustering method, similar to the dynamic clustering algorithm, to generate the MC clusters. Each blob is added to certain cluster with the distance from blob to the center of cluster less than D_I , otherwise create a new cluster and add this blob to it. If the distance between two centers of clusters is less than D_c , they would be merged. Finally clusters are removed if the number of blobs in them is less than N_c . The user-specified parameters D_I , D_c , and N_c are dependent on the image resolution under study.

Fig. 3. FROC curve on the MIAS database.

3 Experiment and Discussion

To evaluate our method for clustered microcalcification detection, we have used the digital mammography dataset provided by the Mammographic Image Analysis Society (MIAS) [1] (the reduced resolution version). This particular database contains 322 images with medio-lateral oblique (MLO) view representing 161 bilateral mammogram pairs, among them 24 images contains 29 microcalcification clusters. Each image has 200 micron pixel edge and the size is 1024×1024 pixels with 8-bit grayscale. It also includes radiologist's truth-markings on the locations of any abnormalities that may be present. These images has no information about x-ray imaging parameters, so they are uncalibrated mammograms.

We have selected 11 images containing 14 clusters as the training set, and other 311 images as the testing set. Contrast marking was done manually on those ROIs which contain microcalcifications, extracted from the training set with four orientations. 1915 samples were collected for training the nonlinear threshold function $f(I_b)$. After applying this threshold function to all mammo-grams of the training set and doing blob generation with $W_m = 5$, we obtained 471 blobs totally. In the virtual biopsy step, we have used 4th order Deubechies wavelets (DB4) to decompose the image blocks for only one level. The size of the support domain was selected as 10×10 . The left figure on Fig. 2 gives subimage around a ROI from image mdb209 before inpainting, after blob removal, and post inpainting. The appearance of the post-repairing blob region is very similar to normal tissues. Blob classifier based on feature space was trained by $C^+ = 0.7$, $C^- = 0.3$. Clustering process was carried out with $D_I = 50$ (10mm), $D_c = 25$ (5mm), and $N_c = 3$.

All 311 test images were processed by the same flow. Fig. 3 shows the FROC curve through changing C^+ and C^- . Overall, it seems that we can achieve the best detection result at 93.3% precision and 4.8 false positives per image. It is, however, not easy to compare the effectiveness of our method to other studies since different work has used different databases or different numbers of mam-

mographic images from the MIAS dataset. Among them, Gulsrud used optimal filters to detect MCs on the MIAS images [10]. But he only tested on 43 images and achieved a true positive (TP) rate of 100% with 2.3 false positives per image, or alternatively TP 100% with one FP cluster per image.

Our initial results on the MIAS dataset suggest that our method could extract clustered microcalcifications effectively and our algorithm is a promising idea for detecting abnormalities on projection medical images. However, the false positive rate is relatively high for practical purposes and has become our current research focus, including the possibilities of introducing image and feature space normalization.

This work is supported in part by HKRGC under HKUST-DAG02/03.EG45.

References

1. Digital mammography database of the mammographic image analysis society. <http://www.wiau.man.ac.uk/services/MIAS/MIASweb.html>.
2. S. Astley, I. Hutt, et al. Automation in mammography: Computer vision and human perception. In *State of The Art in Digital Mammographic Image Analysis*, pages 1–25. World Scientific, 1994.
3. T. Bhangale, U.B. Desai, and U. Sharma. An unsupervised scheme for detection of microcalcifications on mammograms. In *IEEE ICIP*, pages 184–187, 2000.
4. G. Boccignone, A. Chianese, and A. Picariello. Using Renyi's information and wavelets for target detection: An application to mammograms. 3:303–313, 2000.
5. H.P. Chan, S.C. B. Lo, B. Sahiner, K.L. Lam, and M.A. Helvie. Computer-aided detection of mammographic microcalcifications: Pattern recognition with an artificial neural network. *Medical Physics*, 22(10):1555–1567, 1995.
6. T.F. Chan and J. Shen. Inpainting based on nonlinear transport and diffusion. In *Inverse problems, image analysis, and medical imaging*, pages 53–65. 2002.
7. Y. Chitre, A.P. Dhawan, and M. MoskoWitz. Artificial neural network based classification of mammographic microcalcifications using image structure features. In *State of The Art in Digital Mammographic Image Analysis*, pages 167–197. World Scientific, 1994.
8. I. El-Naqa, Y. Yang, M.N. Wernick, N.P. Galatsanos, and R. Nishikawa. A support vector machine approach for detection of microcalcifications in mammograms. In *IEEE ICIP*, pages 201–204, 2002.
9. Y. Freund and R.E. Schapire. Experiments with a new boosting algorithm. In *International Conference on Machine Learning*, pages 148–156, 1996.
10. T.O. Gulsrud, J.H. Husøy, and H. Stavanger. Optimal filter for detection of clustered microcalcifications. In *ICPR*, volume 1, pages 508–511, 2000.
11. J. Jia and C.K. Tang. Image repairing: robust image synthesis by adaptive nd tensor voting. In *IEEE CVPR*, pages 643–650, 2003.
12. S. Mallat. *A Wavelet Tour of Signal Processing*. Academic Press, 1998.
13. T. Netsch. Detection of micro calcification clusters in digital mammograms: A scale space approach. In *IWDM*, 1996.
14. R.N. Strickland and H.I. Hahn. Wavelet transforms for detecting microcalcifications in mammograms. *IEEE TMI*, 15(2):218–229, 1996.
15. V.N. Vapnik. *The Nature of Statistical Learning Theory*. Springer, 2000.

16. W.J.H. Veldkamp and N. Karssemeijer. Accurate segmentation and contrast measurement of mcs in mammograms: a phantom study. *Medical Physics*, 25(7):1102–1110, 1998.
17. W.J.H. Veldkamp and N. Karssemeijer. Normalization of local contrast in mammograms. *IEEE TMI*, 19(7):731–738, 2000.
18. Margaret Yam. *Detection and Analysis of Microcalcification Clusters in X-ray Mammograms Using the hint Representation*. PhD thesis, University of Oxford, 2001.
19. X. Yuan and P.C. Shi. The physical nature of mammographic image processing. Technical report, Biomedical Research Laboratory, Department of Electrical and Electronic Engineering, Hong Kong University of Science and Technology, 2003.
20. O.R. Zaïane, M.-L. Antonie, and A. Coman. Mammography classification by an association rule-based classifier. In *ACM SIGKDD: International Workshop on Multimedia Data Mining*, pages 62–69, 2002.