On Combining Morphological Component Analysis and Concentric Morphology Model for Mammographic Mass Detection

Xinbo Gao, *Senior Member, IEEE*, Ying Wang, Xuelong Li, *Senior Member, IEEE*, and Dacheng Tao, *Member, IEEE*

***Abstract*—Mammographic mass detection is an important task for the early diagnosis of breast cancer. However, it is difficult to distinguish masses from normal regions because of their abundant morphological characteristics and ambiguous margins. To improve the mass detection performance, it is essential to effectively preprocess mammogram to preserve both the intensity distribution and morphological characteristics of regions. In this paper, morphological component analysis is first introduced to decompose a mammogram into a piecewise-smooth component and a texture component. The former is utilized in our detection scheme as it effectively suppresses both structural noises and effects of blood vessels. Then, we propose two novel concentric layer criteria to detect different types of suspicious regions in a mammogram. The combination is evaluated based on the Digital Database for Screening Mammography, where 100 malignant cases and 50 benign cases are utilized. The sensitivity of the proposed scheme is 99% in malignant, 88% in benign, and 95.3% in all types of cases. The results show that the proposed detection scheme achieves satisfactory detection performance and preferable compromises between sensitivity and false positive rates.**

***Index Terms*—Breast cancer, computer-aided detection, mass detection, morphological component analysis (MCA), morphology concentric layer.**

I. Introduction

BREAST cancer is one of the most frequent leading causes of cancer deaths in women. The *American Cancer Society* (ACS) estimates that about 184,450 new breast cancer cases are expected to be diagnosed in 2008 [1]. Therefore, the early detection is a main factor to reduce deaths of the disease. Mammography, which reveals the pronounced evidence of abnormality in breast, is currently the most effective tool for early detection of breast cancer. However, it is difficult to interpret a mammography as its sensitivity is seriously affected by image quality and radiologist's experiences. Independent double reading by two radiologists is introduced in screening routine to improve the accuracy of diagnosis. Though it could improve the sensitivity of diagnosis, the high cost is unacceptable in practical applications. Therefore, *Computer-aided detection* (CAD) schemes have been developed and acknowledged to assist radiologists in improving the accuracy of diagnosis. Masses and calcifications are two primary signatures of abnormity in mammograms. Existing research results show masses are more difficult to recognize because of their abundant appearances and ambiguous margins than calcifications, and thus, mass detection is a challenging problem [2], [3].

A number of schemes have been developed for mammographic mass detection. Early detection schemes always employ simple enhancing or filtering techniques [4]–[6]. To further enhance the detection efficiency and accuracy, some complex techniques are developed. Rangayyan *et al.* [7] studied a density slicing method to segment the *region of interests* (ROIs); Brake and Karssemeijer [8] discussed the mass detection with single- and multiscale styles; Karssemeijer [9] also proposed local orientation patterns for mass detection. To incorporate neighborhood information, Li *et al*. [10] applied the morphological enhancement and stochastic model-based segmentation. Tourassi *et al*. [11] employed ROIs with known ground truth as templates, and the template matching with mutual information was used. Varela *et al.* [12] studied the iris filter in different scales and then developed a new system to detect malignant masses. Their average sensitivities are around 90% at 1–15 *false positives per image* (FPsI).

Recently, essential characteristics of masses are considered for detection. Timp and Karssemeijer [13] investigated interval changes between two consecutive mammographics in the feature space, which could find small lesions and architectural distortions. Georgiou *et al*. [14] studied the original radial distance under the complete spectrum of signal analysis. Guliato *et al*. [15] proposed a method to derive polygonal models of contours to preserve spicules and details of diagnostic importance.

Among all these existing characteristics, gradient and morphological features are most frequently used for masses recognition, since masses always possess a highlighted focal region with some successive dimmer concentric layers. For this reason, Eltonsy *et al*. [16] developed a concentric morphology model for detecting masses. They first granulated the gray

Manuscript received November 20, 2008; revised June 27, 2009. First published November 10, 2009; current version published March 17, 2010. This work was supported by the National Science Foundation of China under Grant 60771068, Grant 60702061, and Grant 60832005, by the Open-End Fund of the National Laboratory of Pattern Recognition in China and the National Laboratory of Automatic Target Recognition, Shenzhen University, China, by the Program for Changjiang Scholars and Innovative Research Team in the University of China under Grant IRT0645, and by the 100 Talents Program of The Chinese Academy of Sciences, by the Nanyang Technological University Nanyang SUG Grant, under Grant M58020010, and by the K. C. Wong Education Foundation Award.

X. Gao and Y. Wang are with the School of Electronic Engineering, Xidian University, Xi'an 710071, China (e-mail: xbgao@mail.xidian.edu.cn; wying@lab202.xidian.edu.cn).

X. Li is with the State Key Laboratory of Transient Optics and Photonics, Xi'an Institute of Optics and Precision Mechanics, Chinese Academy of Sciences, Xi'an 710119, China (e-mail: xuelong_li@opt. ac.cn).

D. Tao is with the School of Computer Engineering, Nanyang Technological University, Singapore 639798, Singapore (e-mail: dctao@ntu.edu.sg).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TITB.2009.2036167

levels of a mammogram into manageable bins; then morphological features were extracted on the granule mammograms; and finally, the suspicious regions were detected by *multiple concentric layers* (MCL) criteria. This scheme takes the essential characteristics of masses into consideration as the preconditions that disclose the real growth activity of masses.

Despite MCL being a promising strategy to detect malignant masses, it is not so suitable for benign cases. This is probably because the strategy only employs a simple gray-level transformation for granulation processing. Despite the fact that the transformation presents the connectivity and similarity among pixels, it leads to three problems: 1) it decreases the global and also local contrast of mammograms, and thus, it is difficult to detect masses with low contrast in comparison with their backgrounds; 2) it assigns granule levels by scanning 3×3 neighborhood of each pixel, and thus, Mosaics effects and morphological features analysis will be incorrect; and 3) it cannot suppress the high intensity of blood vessels and glandular tissues.

To solve the aforementioned problems, we present a new scheme for mass detection. *Morphological component analysis* (MCA) is introduced as a preprocessing step in this scheme to 1) maintain the local contrast of an original mammogram; 2) preserve the margin characteristics; and 3) suppress the structural noises, blood vessels, and glandular tissues. The proposed scheme first decomposes the mammogram into a piecewise-smooth component and a texture component by MCA, where the former component achieves these three objectives. Then, morphological features are extracted and analyzed based on the piecewise-smooth component for detecting ROIs. Finally, ROIs, which satisfy the new concentric layer rules, are extracted as the suspicious mass regions. Model parameters are also discussed for analyzing their impact on detection results and the optimal rules and parameters will be given later.

The rest of this paper is organized as follows. Section II briefs MCA. The proposed framework is detailed in Section III. Experimental results and analysis are given in Section IV and Section V concludes the paper.

II. Morphological Component Analysis

Preprocessing is the precondition and foundation for the mass detection system, so we need a method that could accurately preserve the local contrast and the morphological features of masses in mammograms. Moreover, the method could suppress the negative impaction induced by blood vessels and structural noises. Therefore, MCA is introduced to extract the piecewise-smooth component of mammograms to further improve the detection performance.

MCA [17] separates features that present different morphological aspects contained in an image, and it can be deemed as a fast and simple basis pursuit [18], in which 1) its dictionary is a concatenation associated with a fast transformation and 2) constraints can be easily imposed on decomposed components.

Assume an image s is a linear combination of K components, i.e., $s = \sum_{k=1}^{K} s_k$, and MCA seeks the sparest representation over dictionaries Φ_k, i.e.

$$\left\{\alpha_1^{\mathrm{opt}}, \ldots, \alpha_K^{\mathrm{opt}}\right\} = \arg \min_{\{\alpha_1, \ldots, \alpha_K\}} \sum_{k=1}^{K} \|\alpha_k\|_1 + \lambda \left\| s - \sum_{k=1}^{K} \Phi_k \alpha_k \right\|_2^2 \tag{1}$$

where α_k represents the kth sparse solution. To have a fast solving procedure, MCA uses dictionaries that have a fast transformation T_k ($\alpha_k = \mathrm{T}_k s_k$) and reconstruction R_k ($s_k = \mathrm{R}_k \alpha_k$). Then, the problem is simplified as

$$\left\{s_1^{\mathrm{opt}}, \ldots, s_K^{\mathrm{opt}}\right\} = \arg \min_{\{s_1, \ldots, s_K\}} \sum_{k=1}^{K} \|\mathrm{T}_k s_k\|_1 + \lambda \left\| s - \sum_{k=1}^{K} s_k \right\|_2^2. \tag{2}$$

Block coordinate relaxation method [19] can be utilized to obtain the solution of (2). Based on MCA, an image is decomposed into different components by using different combinations of transformations and each component represents a kind of morphologic component.

III. Mass Detection Based on MCA and Modified MCL

The proposed scheme comprises three major stages, i.e., preprocessing, morphological feature extraction, and rule-based detection stage. Fig. 1 shows the overview of the proposed mass detection scheme, each component of which will be described in detail as follows.

A. MCA in Mammograms

A mammogram can be deemed as a combination of two components, a piecewise-smooth component that contains main energy and intensity distribution of the breast region, and a texture component that contains blood vessels and structural noises. Therefore, we need two dictionaries to, respectively, represent these components in mammograms.

Undecimated version of *biorthogonal wavelet transforms* (UWT) is often well suited to a wide class of natural scenes [20]. It can effectively represent the piecewise-smooth content in images. In addition, the shift invariance property of UWT could make the mass location process more accurate. So, the UWT is applied in our decomposition work. *Local discrete cosine transform* (LDCT) possesses good performance in extracting the local texture. It can effectively represent either smooth or periodic behaviors [20]. Thus, LDCT is adopted to extract the structural noises and blood vessels in mammogram.

Assume $\mathrm{T}_{\mathrm{LDC}}$ and $\mathrm{T}_{\mathrm{UWT}}$ denote the UWT and LDCT, respectively. Under this setting, the solutions are given by $\left\{\alpha_{\mathrm{LDC}}^{\mathrm{opt}}, \alpha_{\mathrm{UWT}}^{\mathrm{opt}}\right\}$, and we can get two components s_{LDC} and s_{UWT}. Therefore, (2) is rewritten as

$$\left\{s_{\mathrm{LDC}}^{\mathrm{opt}}, s_{\mathrm{UWT}}^{\mathrm{opt}}\right\} = \arg \min_{\{s_{\mathrm{LDC}}, s_{\mathrm{UWT}}\}} \|\mathrm{T}_{\mathrm{LDC}} s_{\mathrm{LDC}}\|_1 + \|\mathrm{T}_{\mathrm{UWT}} s_{\mathrm{UWT}}\|_1 + \lambda \|s - s_{\mathrm{LDC}} - s_{\mathrm{UWT}}\|_2^2. \tag{3}$$

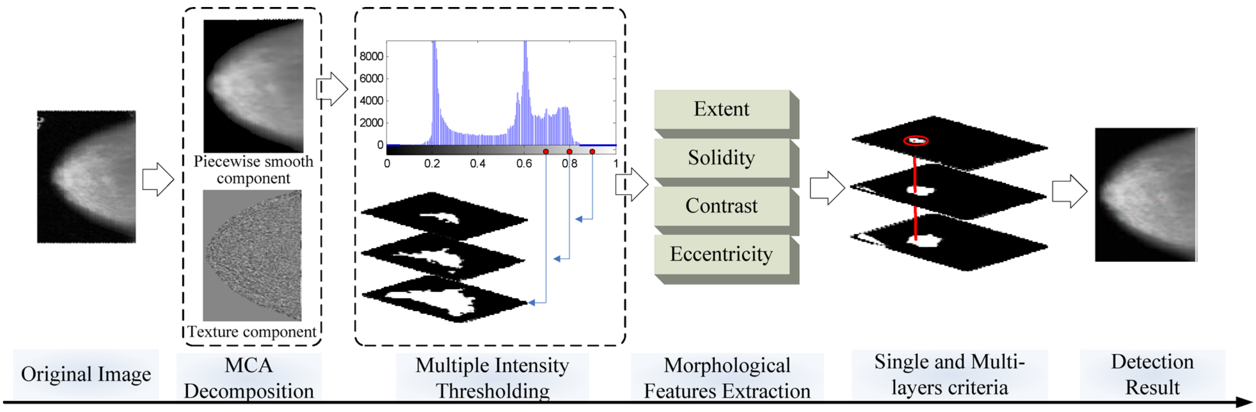


Fig. 1. Proposed mass detection scheme.

We also apply the block coordinate relaxation to obtain the optimal solution of (3) and the details are given as follows.

Step 1: Initialize the number of iterations N and threshold $\delta = \lambda N$.

Step 2: In each iteration, if $\delta > \lambda$

1) update s_{LDC} with fixed s_{UWT};
2) calculate the residual $r = s - s_{\mathrm{UWT}}$ and transform r to obtain α_{LDC};
3) soft threshold is used to obtain $\hat{\alpha}_{\mathrm{LDC}}$, and the signal is reconstructed by $s_{\mathrm{LDC}} = \mathrm{R}_{\mathrm{LDC}}\hat{\alpha}_{\mathrm{LDC}}$;
4) assume s_{LDC} is fixed and repeat the above operation.

Then, morphologic features will be extracted based on the piecewise-smooth component, described as follows.

B. Morphological Features Extraction and Analysis

Most mass regions always possess rounded or oval focal areas, and the intensity distributions within them are usually continuous. These experiences provide some useful morphological features to detect the ROIs, through which regions with high suspicion could be detected.

1) Solidity: It describes duty ratio by calculating the ratio of the filling area to the total area including all the holes of the region. Since mass regions always possess continuous intensity distributions, their solidity values are very high. Variations of this parameter almost do not affect the detection sensitivities, while it may affect the false positive rates subtlety.

2) Eccentricity: It represents the region shapes. It is the eccentricity of the ellipse that is most close to the region. Focal regions of masses always possess rounded or oval shapes. So, regions are potentially mass regions when this parameter is more than the threshold. This parameter is very important in the detection procedure, since a little variation will severely affect the sensitivity and the FPsI.

3) Extent: This parameter is the ratio of an actual area to its smallest external rectangle. Normal regions always possess arbitrary shapes which are more likely anisotropic, while focal regions of masses usually have large extent value because of their rounded or oval shapes. This parameter affects detection results severely, and a small threshold will bring many false positives.

4) Contrast: It is the intensity ratio of a focal region to its inflated region. Some small masses do not have concentric layers, so this parameter can help in detecting small masses. In addition, this parameter also affects the detection performance, and an appropriate threshold can improve the sensitivity.

C. Mass Region Detection

Mass regions always possess continuous intensity distributions. They usually have the brightest focal regions and then gradually grow dimmer. Therefore, after mammograms are separated into multi-intensity layers by using different intensity thresholds, the real mass regions should contain some concentric layers on different intensity layers. MCA extract the piecewise-smooth component of mammograms, but this operation also reduces the multilayer characteristic of masses' intensity. Therefore, suspicious region detection criteria should be modified according to the practical detection procedures.

According to the smooth degree of mammograms obtained by MCA, masses can be divided into two major classes, i.e., large masses with more than one concentric layer and small masses with no concentric layers. Then, we develop two new detection criteria for mass region detection.

1) Multilayer Criterion: Focal regions with concentric layers ($\geq$1) are considered as mass regions, and the confidence increases with the increase in the number of layers.

2) Single-Layer Criterion: Focal regions without concentric layers in their adjacent lower intensity layer are considered as mass regions, only if their morphological features satisfy stricter threshold conditions and the additional contrast condition at the same time.

These two criteria cover two types of masses. One is the mass regions with significant intensity distributions, and another type is the subtle abnormities that possess a small area with weak contrast. Therefore, these two new criteria are developed to detect all types of mass regions. If one of the criteria is satisfied, the region can be deemed as the suspicious region.

As described earlier, the detailed procedure of the proposed detection scheme is given as follows.

Step 1: Breast regions are segmented first by using Otsu's method. Then, the mammograms are decomposed into piecewise-smooth component and textural component by using MCA.

Step 2: Piecewise-smooth parts of mammograms are then separated into different intensity layers by using multiple intensity thresholds. The thresholds start from the highest gray level to the lowest one with a predefined fixed step. All the independent regions in each intensity layer are then extracted for further analysis. The separation is stopped when the area of the thresholding regions is larger than half of the size of the mammograms.

Step 3: Morphological features in B are calculated to select the suspicious focal regions. We preserve regions, which satisfy all the initial conditions, as suspicious focal regions.

Step 4: After initial selection, unnecessary regions are further removed by using two new concentric layer criteria.

Finally, false positives are removed by using criteria of the MCL method, and the ultimate detection results are given.

IV. Experimental Results and Analysis

A. Dataset

The scheme is tested with a total of 200 mammograms selected from the DDSM provided by the University of South Florida [21]. Mammograms in DDSM were digitized by using the Lumisys scanner at 0.5 mm, and Howtek scanner at 0.435 mm pixel size, 12 bits per pixel, with size about 5000 pixel $\times$ 3000 pixel. Mammograms containing suspect areas have associated ground truth information about the locations and types of those regions. The subdatabases that were selected include circumscribed and speculate cases in both benign and malignant categories. Among all the cases, 140 are malignant masses while 60 are benign ones, and 50 (40 malignant and 10 benign) are selected as the training set to analyze the model parameters. Before the scheme was applied, mammograms were downsampled by a factor of 5. Since masses always possess certain area, the downsampling operation will affect the performance slightly while the processing will be speeded up significantly.

B. Model Parameters Analysis

As described in Section III, model parameters in each step play an important role in the whole detection scheme. These parameters are discussed independently. In this paper, we pay more attention to sensitivity because it is more important at the detection stage.

1) Layer Separation Interval (LSI)*:* It was set as 0.05 in our detection scheme, which resulted in a good tradeoff between the sensitivity and false positives rates. Table I shows the detection results under different settings in training.

TP is the true positive rate of the detection results. According to the training results in Table II, 0.05 is a good choice of LSI and it led to better compromise between TP and FPsI.

2) Morphological Features: These parameters are initial conditions for ROIs selection. Among them, solidity affects the false positives rate subtlety, while eccentricity and extent not only affect the false positive rate but also the sensitivity. Figs. 2 and 3 show the sensitivities and FPsI with different thresholds, respectively.

TABLE I
DETECTION RESULTS UNDER DIFFERENT LSIs

LSI	Cancer Cases (TP / FPsI)	Benign Cases (TP / FPsI)	All Cases (TP / FPsI)
0.01	100.0% / 8.5	90.0% / 7.9	98.0% / 8.4
0.03	100.0% / 3.7	90.0% / 4.2	98.0% / 3.8
0.05	100.0% / 2.0	80.0% / 1.7	96.0% / 1.9
0.07	75.0% / 1.6	60.0% / 1.4	72.0% / 1.5
0.09	55.0% / 0.9	50.0% / 1.0	54.0% / 0.9
0.10	50.0% / 0.6	50.0% / 0.5	50.0% / 0.5

TABLE II
DETECTION RESULTS UNDER DIFFERENT MLCs

MLc	Cancer Cases (TP / FPsI)	Benign Cases (TP / FPsI)	All Cases (TP / FPsI)
1	77.5% / 0.9	50.0% / 0.4	72.0% / 0.8
2	25.0% / 0.2	10.0% / 0.0	22.0% / 0.2
3	5.0% / 0.0	0.0% / 0.0	4.0% / 0.0

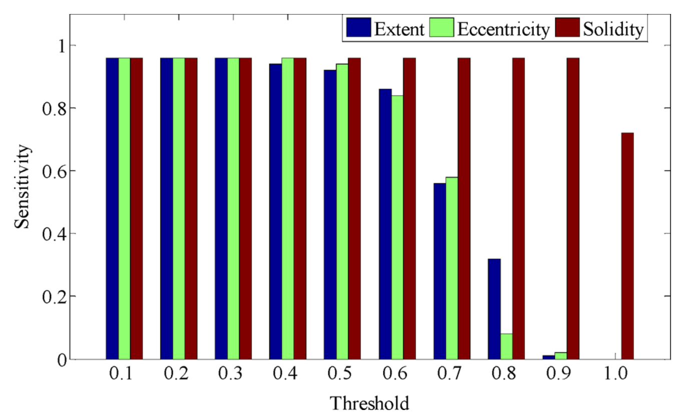


Fig. 2. Sensitivity with different thresholds of initial selection.

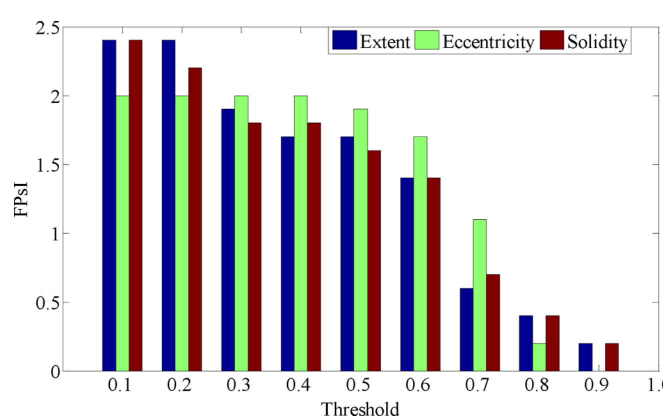


Fig. 3. FPsI with different thresholds of initial selection.

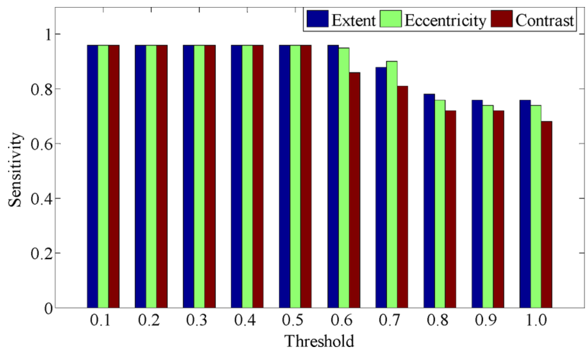


Fig. 4. Sensitivity with different thresholds of SLc.

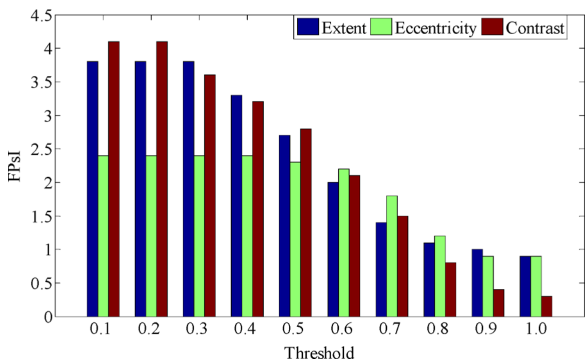


Fig. 5. FPsI with different thresholds of SLc.

3) Multiconcentric Layers Criteria (MLc)*:* If selected ROIs have more than one concentric layer in their successive lower intensity layers, they will be considered as mass regions. When criteria turn strict, the detection sensitivity deceases. The corresponding detection results without single-layer criteria are shown in Table II. Without the single-layer criteria, the detection results are unacceptable.

4) Single-Layer Criteria (SLc)*:* Smaller masses are easily missed by using only the multiple concentric layers criteria, and thus, single-layer criteria is developed to detect small masses. Here, only eccentricity and extent are considered because area and solidity contribute little to sensitivity. Furthermore, contrast is used to ensure the experienced assumption that mass regions always possess a highlighted focal region and evolving concentric layers grow dimmer. Figs. 4 and 5 show the detection performance of the training set.

5) False Positives Reduction Criteria: The relative incidence and minimum distance criteria are used to reduce the false positives. These two parameters affect the detection performance slightly as focal regions are always much smaller than the other detected isolated regions in the same intensity layer. Besides this, minimum distance does not work in our scheme as once regions are determined as concentric regions in high intensity layers, they will not affect other selection activities. However, these two criteria will decrease the FPsI about 0.1–0.4.

According to the earlier discussions and analyses, we can determine a group of reasonable model parameters. Table III

TABLE III
OPTIMAL PARAMETER SETTINGS IN DETECTION SCHEME

Model Parameters	Optimal Setting	Detection Performance (TP / FPsI)
LSI	0.05	96.0% / 1.9
Solidity	0.90	96.0% / 1.9
Eccentricity	0.40	96.0% / 2.0
Extent	0.30	96.0% / 1.9
MLc	1.00	72.0% / 0.8
SLc (Extent)	0.60	96.0% / 2.0
SLc (Eccentricity)	0.50	96.0% / 2.3
SLc (Contrast)	0.50	96.0% / 2.1

TABLE IV
MODEL PARAMETER SETTINGS IN DIFFERENT METHODS

Model Parameters	Original MCL Method	Mending Parameters in MCL I	Mending Parameters in MCL II	Our Method
LSI	0.05	0.05	0.05	0.05
Solidity	0.25	0.90	0.90	0.90
Eccentricity	0.49	0.40	0.40	0.40
Extent	0.26	0.30	0.30	0.30
MLc	3	1	1	1
SLc (Extent)	-	-	0.60	0.60
SLc (Eccentricity)	-	-	0.50	0.50
SLc (Contrast)	-	-	0.50	0.50

TABLE V
DETECTION RESULTS USING DIFFERENT METHODS

Methods	Cancer Cases (TP / FPsI)	Benign Cases (TP / FPsI)	All Cases (TP / FPsI)
Original MCL	59.0% / 1.8	50.0% / 1.6	56.0% / 1.73
Mending Parameters in MCL I	87.0% / 7.4	80.0% / 8.1	84.7% / 7.63
Mending Parameters in MCL II	93.0% / 10.1	88.0% / 11.0	91.3% / 10.40
Our Method	99.0% / 2.7	88.0% / 3.1	95.3% / 2.83

shows the final settings of all parameters used in our mass detection scheme.

C. Mass Detection Results

For comparison with the original MCL method, we first simulate the MCL method using the whole settings and conditions as it used in [16]. However, we failed to get reasonable results due to a different database employed in our experiments. Therefore, the settings and thresholds were changed to get comparative results as they are in [16]. Table IV gives the settings in MCL and our method, respectively.

Following the settings in Table IV, the detection results on the test set with 150 mammograms are given in Table V. As shown in Table V, the proposed scheme could improve the detection sensitivity by about 6% for cancer cases and get comparative results with the mending MCL method for benign cases. Furthermore, it is more effective on removing false positives.

The main intermediate procedures of the detection scheme are shown in Fig. 6. First, the mammograms are decomposed by MCA method, and only the smooth components are reserved for

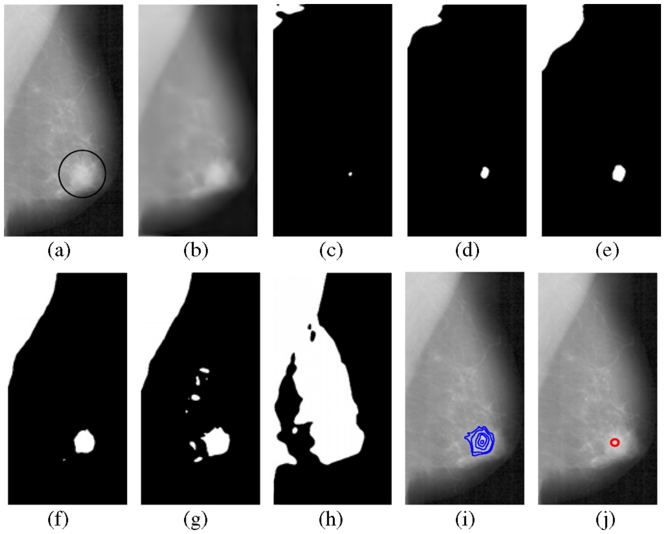


Fig. 6. Whole process of the detection scheme. (a) Original image. (b) Piecewise-smooth image. (c) First density layer. (d) Second density layer. (e) Third density layer. (f) Fourth density layer. (g) Fifth density layer. (h) Eighth density layer. (i) Multilayer characteristics of the mass regions. (j) Detection result.

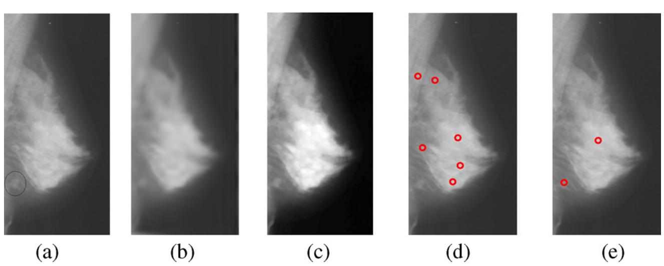


Fig. 7. Detection results. (a) Original image. (b) Piecewise-smooth image. (c) Granule image. (d) Detection result based on MCL without employing MCA. (e) Detection result based on MCA.

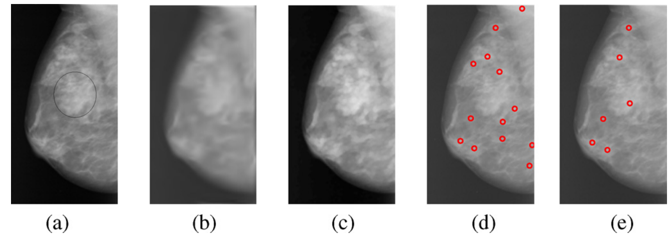


Fig. 8. Detection results. (a) Original image. (b) Piecewise-smooth image. (c) Granule image. (d) Detection result based on MCL without employing MCA. (e) Detection result based on MCA.

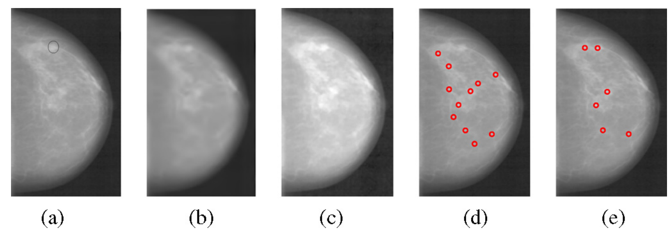


Fig. 9. Detection results. (a) Original image. (b) Piecewise-smooth image. (c) Granule image. (d) Detection result based on MCL without employing MCA. (e) Detection result based on MCA.

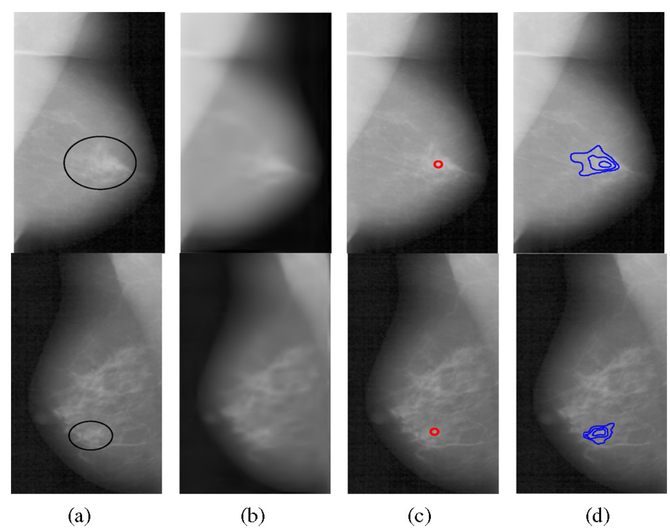


Fig. 10. Detection results of malignant cases. (a) Original image. (b) Piecewise-smooth image. (c) Detection result based on MCL. (d) Multilayer characteristics of the mass regions.

later detection. Then, the density layers with different thresholds are acquired for picking up the suspicious isolated regions. And the regions which could satisfy the morphological limitations and also the density layer criteria are finally detected as the mass regions.

The original MCL method without employing MCA method cannot detect the weak contrast regions [as shown in Fig. 7(d)], while the new detection scheme can accurately detect them [as shown in Fig. 7(e)].

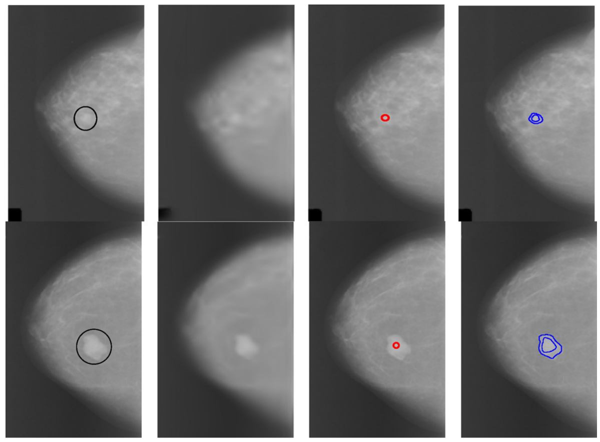
A granule image without using MCA is given in Fig. 8(c), which presents obvious Mosaic effects. The detection result based on it is given in Fig. 8(d). As we can see, the real mass region is missed. The detection result based on MCA is shown in Fig. 8(e), which can accurately detect the missed abnormity.

Masses are different to detect in mammograms based on granulation processing because it cannot suppress the blood vessels and structural noises. The detection result using MCA is given in Fig. 9(e), and the abnormity is accurately detected as the highlight margin of blood vessels and structural noises are suppressed by MCA.

Then, the detection results of the malignant and benign cases are presented, respectively. As shown in Figs. 10 and 11, the malignant masses always possess complex density distributions, while the benign cases have more homogeneous density distributions with well-defined margins. And the proposed detection scheme could effectively detect both these cases.

Although the proposed scheme can improve the detection performance significantly with lower false positives rates, it fails to work well on the following examples, as shown in Fig. 12. These missed cases always possess dense glandular tissues embedded with mass regions.

The missed mass regions, as shown in Fig. 12, are similar to circles or ellipses with highest density in the center, i.e., the intensity distributions of these mass regions are similar to 2-D projection of Gaussian surface. Therefore, the Gaussian



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

Fig. 11. Detection results of benign cases. (a) Original image. (b) Piecewise-smooth image. (c) Detection result based on MCL. (d) Multilayer characteristics of the mass regions.

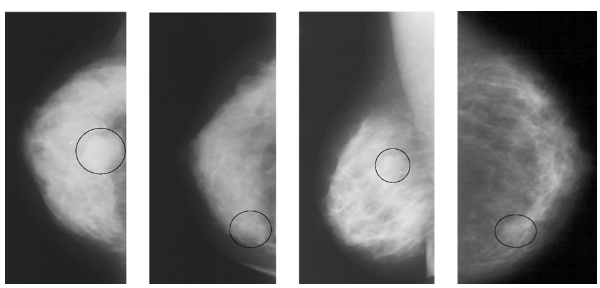
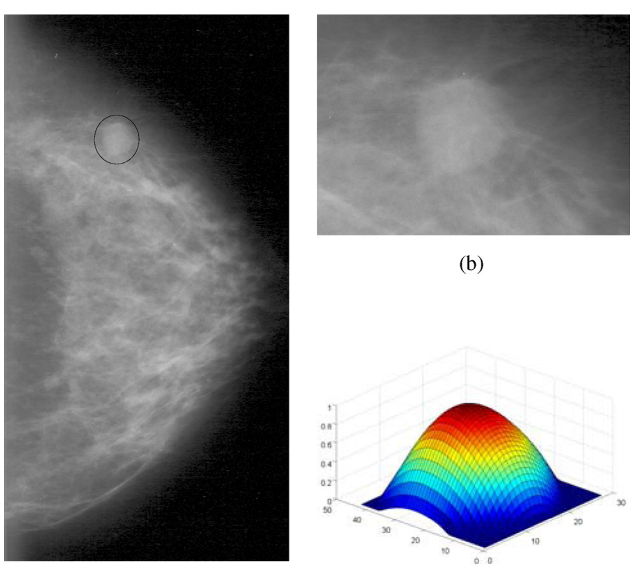


Fig. 12. Missed cases.



(a) (b) (c)

Fig. 13. Mass intensity distribution. (a) Original image. (b) Subimage with a mass region. (c) 3-D intensity distribution of the mass region.

model could be introduced to effectively represent this common characteristic of these mass regions, as shown in Fig. 13. In the future, we will consider using the Gaussian model to further enhance the performance of the proposed scheme.

V. Conclusion

A novel mass detection scheme based on MCA and new concentric layer criteria is presented in this paper. The scheme first decomposes the mammograms into piecewise-smooth component and texture component by using MCA. Then, the smooth component is used to extract the independent regions on different intensity layers. Four morphological features are calculated to initially select ROIs, and selected regions are considered as mass regions when they satisfy one of the concentric layer criteria. Finally, two false positives reduction criteria are developed to control the number of FPsI. The experimental results show that the proposed concentric layer criteria could effectively improve the detection sensitivity of the benign masses, and the MCA-based mass detection scheme could achieve satisfactory detection sensitivity with acceptable FPsI. Though the model parameters of the scheme are discussed to decide the optimal settings, more robust method should be developed to get the generalized model. Furthermore, new features such as Gaussian distribution characteristics of mass regions and local texture should be introduced to further reduce the false positives.

Acknowledgment

The authors thank the anonymous reviewers for their helpful comments and suggestions.

References

[1] American Cancer Society. (2008). "Cancer facts and figures 2008," in *Statistics for 2008*. [Online]. Available: http://www.cancer.org/downloads/STT/008-CAFFfinalsecured.pdf

[2] M. P. Sampat, M. K. Markey, and A. C. Bovik, "Computer-aided detection and diagnosis in mammography," in *Handbook of Image and Video Processing*, 2nd ed. New York: Academic, 2005, pp. 1195–1217.

[3] R. M. Rangayyan, F. J. Ayres, and J. E. Leo Desautels, "A review of computer-aided diagnosis of breast cancer: Toward the detection of subtle signs," *J. Franklin Inst.*, vol. 344, no. 3–4, pp. 312–348, May/Jul. 2007.

[4] N. Petrick, H. P. Chan, B. Sahiner, and D. Wei, "An adaptive density-weighted contrast enhancement filter for mammographic breast mass detection," *IEEE Trans. Med. Imag.*, vol. 15, no. 1, pp. 59–67, Feb. 1996.

[5] R. M. Rangayyan, L. Shen, Y. Shen, J. E. Leo Desautels, H. Bryant, T. J. Terry, N. Horeczko, and M. S. Rose, "Improvement of sensitivity of breast cancer diagnosis with adaptive neighborhood contrast enhancement of mammograms," *IEEE Trans. Med. Imag.*, vol. 16, no. 3, pp. 161–170, Sep. 1997.

[6] H. Kobatake, M. Murakami, H. Takeo, and S. Nawano, "Computerized detection of malignant tumors on digital mammograms," *IEEE Trans. Med. Imag.*, vol. 18, no. 5, pp. 369–378, May 1999.

[7] N. R. Mudigonda, R. M. Rangayyan, and J. E. Leo Desautels, "Detection of breast masses in mammograms by density slicing and texture flow-field analysis," *IEEE Trans. Med. Imag.*, vol. 20, no. 12, pp. 1215–1227, Dec. 2001.

[8] G. M. te Brake and N. Karssemeijer, "Single and multiscale detection of masses in digital mammograms," *IEEE Trans. Med. Imag.*, vol. 18, no. 7, pp. 628–639, Jul. 1999.

[9] N. Karssemeijer, "Local orientation distribution as a function of spatial scale for detection of masses in mammograms," in *Proc. IPMI*, Lecture Notes in Computer Science, 1999, vol. 1613, pp. 280–293.

[10] H. Li, Y. Wang, K. J. R. Liu, S. B. Lo, and M. T. Freedman, "Computerized radiographic mass detection—part I: Lesion site selection by morphological enhancement and contextual segmentation," *IEEE Trans. Med. Imag.*, vol. 20, no. 4, pp. 289–301, Apr. 2001.

[11] G. D. Tourassi, R. V. Voracek, D. M. Catarious, Jr., and C. E. Floyd, Jr., "Computer-assisted detection of mammographic masses: A template matching scheme based on mutual information," *Med. Phys.*, vol. 30, no. 8, pp. 2123–2130, Aug. 2003.

[12] C. Varela, P. G. Tahoces, A. J. Méndez, M. Souto, and J. J. Vidal, "Computerized detection of breast masses in digitized mammograms," *Comput. Biol. Med.*, vol. 37, no. 2, pp. 214–226, Feb. 2007.

[13] S. Timp and N. Karssemeijer, "Interval change analysis to improve computer aided detection in mammography," *Med. Image Anal.*, vol. 10, no. 1, pp. 82–95, Feb. 2006.

[14] H. Georgiou, M. Mavroforakis, N. Dimitropoulos, D. Cavouras, and S. Theodoridis, "Multi-scale morphological features for the characterization of mammographic masses using statistical classification schemes," *Artif. Intell. Med.*, vol. 41, no. 1, pp. 39–55, Sep. 2007.

[15] D. Guliato, R. M. Rangayyan, J. D. Carvalho, and S. A. Santiago, "Polygonal modeling of contours of breast tumors with the preservation of spicules," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 1, pp. 14–20, Jan. 2008.

[16] N. H. Eltonsy, G. D. Tourassi, and A. S. Elmaghraby, "A concentric morphology model for the detection of masses in mammography," *IEEE Trans. Med. Imag.*, vol. 26, no. 6, pp. 880–889, Jun. 2007.

[17] J. L. Starck, M. Elad, and D. Donoho, "Redundant multiscale transforms and their application for morphological component analysis," *Adv. Imag. Electron Phys.*, vol. 132, pp. 287–348, Feb. 2004.

[18] S. Chen, D. Donoho, and M. Saunder, "Atomic decomposition by basis pursuit," *SIAM J. Sci. Comput.*, vol. 20, no. 1, pp. 33–61, Jan. 1998.

[19] A. Bruce, S. Sardy, and P. Tseng, "Block coordinate relaxation methods for nonparametric signal denoising," in *Proc. Int. Soc. Opt. Eng. (SPIE)*, 1998, vol. 3391, pp. 75–86.

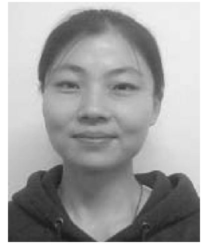
[20] J. L. Starck, M. Elad, and D. L. Donoho, "Image decomposition via the combination of sparse representations and a variational approach," *IEEE Trans. Image Process.*, vol. 14, no. 10, pp. 1570–1582, Oct. 2005.

[21] University of South Florida. (2004). *Digital Database for Screening Mammography (DDSM)*. [Online]. Available: http://marathon.csee.usf.edu/Mammography/Database.html

Xinbo Gao (M'02–SM'07) received the B.Sc., M.Sc., and Ph.D. degrees in signal and information processing from Xidian University, Xi'an, China, in 1994, 1997, and 1999, respectively.

From 1997 to 1998, he was a Research Fellow with the Department of Computer Science, Shizuoka University, Shizuoka, Japan. From 2000 to 2001, he was a Postdoctoral Research Fellow with the Department of Information Engineering, The Chinese University of Hong Kong, Shatin, Hong Kong. Since 2001, he has been with the School of Electronic Engineering, Xidian University, where he is currently a Professor of pattern recognition and intelligent system and the Director of the Video and Image Processing System (VIPS) Laboratory. He has published four books and more than 100 scientific papers in refereed journals and proceedings, including the IEEE TRANSACTIONS ON IMAGE PROCESSING, the IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY, the IEEE TRANSACTIONS ON NEURAL NETWORKS, the IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—PART C: APPLICATIONS AND REVIEWS, etc. His research interests include computational intelligence, machine learning, computer vision, pattern recognition, and artificial intelligence.

Prof. Gao is a Fellow of the Institution of Engineering and Technology (IET). He is on the Editorial Boards of many journals, including *EURASIP Signal Processing* (Elsevier) and *Neurocomputing* (Elsevier). He served as General Chair/Co-Chair or Program Committee Chair/Co-Chair or PC member for around 30 major international conferences. He is a member of the IEEE Xi'an Section Executive Committee, the Membership Development Committee Chair, and the Vice Chairman of IET Xi'an Network.



Ying Wang received the B.Sc. degree in 2003 and the M.Sc. degree in 2006, both in signal and information processing, from Xidian University, Xi'an, China, where she is currently working toward the Ph.D. degree in pattern recognition and intelligence system.

Her research interests include medical image analysis, pattern recognition, and computer-aided diagnosis.

Xuelong Li (M'02–SM'07) is a Researcher (Full Professor) with the State Key Laboratory of Transient Optics and Photonics, Xi'an Institute of Optics and Precision Mechanics, Chinese Academy of Sciences, Xi'an, China.

Dacheng Tao (M'07) received the B.Eng. degree from the University of Science and Technology of China, the M.Phil degree from The Chinese University of Hong Kong, Shatin, Hong Kong, and the Ph.D. degree from the University of London, London, U.K.

Currently, he is a Nanyang Assistant Professor with the School of Computer Engineering, Nanyang Technological University, Singapore, and holds a visiting post in London. He is a Visiting Professor at Xidian University, Xi'an, China, and a Guest Professor at Wuhan University, Wuhan, China. He has published more than 100 scientific papers in top venues with best paper runner up awards and finalists. He has authored/edited six books and eight journal special issues. His research is mainly on applying statistics and mathematics for data analysis problems in computer vision, multimedia, machine learning, data mining, and video surveillance.

He has Cochaired for special sessions, invited sessions, workshops, panels and conferences. He is an Associate Editor of the IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING and the *Computational Statistics and Data Analysis* (Elsevier).