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Detection of microcalcifications in digital mammograms using wavelet filter and Markov random field model

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Abstract

Clustered microcalcifcations (MCs) in digitized mammograms has been widely recognized as an early sign of breast cancer in women. This work is devoted to developing a computer-aided diagnosis (CAD) system for the detection of MCs in digital mammograms. Such a task actually involves two key issues: detection of suspicious MCs and recognition of true MCs. Accordingly, our approach is divided into two stages. At first, all suspicious MCs are preserved by thresholding a filtered mammogram via a wavelet filter according to the MPV (mean pixel value) of that image. Subsequently, Markov random field parameters based on the Derin–Elliott model are extracted from the neighborhood of every suspicious MCs as the primary texture features. The primary features combined with three auxiliary texture quantities serve as inputs to classifiers for the recognition of true MCs so as to decrease the false positive rate. Both Bayes classifier and back-propagation neural network were used for computer experiments.

The data used to test this method were 20 mammograms containing 25 areas of clustered MCs marked by radiologists. Our method can readily remove 1341 false positives out of 1356, namely, 98.9% false positives were removed. Additionally, the sensitivity (true positives rate) is 92%, with only 0.75 false positives per image. From our experiments, we conclude that, with a proper choice of classifier, the texture feature based on Markov random field parameters combined with properly designed auxiliary features extracted from the texture context of the MCs can work outstandingly in the recognition of MCs in digital mammograms.

Keywords: Microcalcifications; Mammograms; Markov random field; Wavelet representation; Bayes classifier; Back-propagation neural network

1. Introduction

Breast cancer has been widely recognized as one of the most frequent, malignant tumors in women. For early detection of breast cancer, mammography is often regarded as more effective than other imaging modalities in exposing the indirect sign of malignancy—microcalcifications (MCs) in the breast tissues. Nevertheless, raw mammogram images are not apt to human perception in distinguishing normal glandular tissues and malignant disease [1], especially when the images are obtained from younger women who have denser breast tissues. This is mainly due to two problems: (1) *low contrast* between MCs and the surrounding tissues in the raw mammogram images, which leads to *difficulty in spotting suspect MCs*; and (2) *high false positive rate* in the final MC classification. Both problems are further aggravated by the highly variant sizes and shapes of MCs. Therefore, computer-aided analysis is crucial for digital mammograms.

Many methods have been proposed to increase the contrast of MC clusters and normal tissues in mammogram images. One school of research works focused on manifesting the MC regions in the image. For example, Gordon and Rangayyan [2] proposed a local enhancement method which took advantage of the statistical characteristics of the neighborhood of each pixel. Although this method overcomes the drawback of the global enhancement method [3], it cannot adapt to varying sizes and shapes

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typically found in MC clusters. To this end, Morrow et al. [4] suggested an adaptive-neighborhood technique to enhance the identification of MC clusters. However, the scheme requires both high-resolution digitization of mammograms and high-resolution processing procedures, which is often impractical in typical deployment.

The other school of research works focused on removing the background noise so as to increase the contrast. For example, Lai et al. [5] investigated a *selective median* filtering, in which the tradeoff between noise removal and edge preservation is embedded in the decision of the filtering threshold. Zhao [6] employed morphology to remove the background noise. But this method requires a prior knowledge of the size and shape of MC clusters, which is often not available during initial identification. Zhao et al. [7] also employed an adaptive threshold function from morphological operations in conjunction with a rule base provided by expert radiologist to identify suspected MC clusters for further clinical diagnosis. Strickland and Hahn [8] developed a two-stage method based on wavelet transform for detecting and segmenting MC clusters. They demonstrated that with proper wavelet basis, the detection of MCs can be easily achieved and a straightforward thresholding can be applied to segment them. Following [8], Wang and Karayiannis [9] presented an MC detection method that consisted of decomposing the mammogram into different frequency subbands, suppressing the low-frequency subband, and finally, reconstructing the mammogram from the subbands containing only high frequencies.

Meanwhile, research works have also been conducted to tackle the high false rate problem in final MC classification. For example, Zheng et al. [10] proposed a mixed-feature-based neural network (MFNN) using spectral entropy as the decision criterion to detect MC clusters. Yu and Guan [11] extracted 31 features (mean, variance, contrast, shape, etc.) and employed a general regressive neural network (GRNN) to detect clustered MCs. Gulsrud and Husoy [12] used a filter optimized with respect to the Fisher criterion to extract texture features for the distinction between MCs and normal tissues. El-Naqa et al. [13] employed support vector machines (SVM) to detect MCs and proposed a successive enhancement learning scheme to reduce the false positives.

This paper proposes a two-stage computer-aided image analysis method to overcome the two main problems in the detection of MCs in mammograms, namely the *low contrast* between the MCs and the surrounding breast tissue and the *high false positive rate* in MCs classification. In the first stage, a *wavelet filter* is utilized to remove the background noise and preserve all the suspicious MCs in the images. In the second stage, Markov random field parameters are used to enhance the recognition of 'true' MCs and thus reduce the false positives rate. A group of 20 mammograms from the MiniMammographic Database provided by the Mammographic Image Analysis Society [14] is used to verify the effectiveness of the proposed method.

The rest of this paper is organized as follows: Section 2 presents a brief description of mathematical foundation of wavelet analysis and Markov random field model. Section 3 describes the method of suspicious MCs detection, feature extraction, and classification. Section 4 presents our experimental results and the related discussion. Section 5 is the conclusion remarks of this study.

2. Theoretical background

2.1. Multiresolution representation of signal with wavelets

The microcalcifications (MCs) in mammograms usually appear in small clusters of a few pixels with relatively high intensity. In this regard, wavelet transform presents an excellent analysis tool since it uses shorter windows at high frequencies and long windows at low frequencies, which effectively separates the high frequency MCs from the low frequency background tissues in the mammograms. In the following, we briefly review the theory of wavelet representation needed in this paper [15–18].

2.1.1. One-dimensional wavelet representation

The *multiresolution approximation* of a one-dimensional signal $f(x)\in\mathbf{L}^2(\mathbf{R})$ at a resolution 2^m is defined as the orthogonal projecting of such a signal on a subspace $\mathbf{V}_m$ of $\mathbf{L}^2(\mathbf{R})$. Heuristically and theoretically, the approximation $A_{m+1}f(x)$ at resolution 2^{m+1} contains more information than the approximation $A_mf(x)$ at resolution 2^m. The *detail signal* of $f(x)$ at resolution 2^m, denoted by $D_mf(x)$, is defined as the difference of $A_{m+1}f(x)$ and $A_mf(x)$. Accordingly, $D_mf(x)$ is equivalent to the orthogonal projection of $f(x)$ on the complement $\mathbf{U}_m$ of vector space $\mathbf{V}_m$ in $\mathbf{V}_{m+1}$.

According to the theory of multiresolution signal decomposition [16], there exists a unique *scaling function* $\phi(x)\in\mathbf{L}^2(\mathbf{R})$ and a unique corresponding *wavelet function* $\psi(x)\in\mathbf{L}^2(\mathbf{R})$, associated with $\phi_m(x)=2^m\phi(2^mx)$ and $\psi_m(x)=2^m\psi(2^mx)$, such that $\left\{\sqrt{2^{-m}}\phi_m(x-2^{-m}n)\right\}_{n\in Z}$ and $\left\{\sqrt{2^{-m}}\psi_m(x-2^{-m}n)\right\}_{n\in Z}$ are orthonormal bases of $\mathbf{U}_m$ and $\mathbf{V}_m$, respectively. In this sense, the approximation and detail signals of the original signal $f(x)$ at resolution 2^m are completely characterized by the sequence of inner products of $f(x)$ with ϕ_m and ψ_m, respectively

$$\{A_mf(n)\}_{n\in Z}=\{\langle f(u),\phi_m(u-2^{-m}n)\rangle\}_{n\in Z}, \tag{1}$$

and

$$\{D_mf(n)\}_{n\in Z}=\{\langle f(u),\psi_m(u-2^{-m}n)\rangle\}_{n\in Z}. \tag{2}$$

Define $h(n)=\langle\phi_{-1}(x),\phi(x-n)\rangle$ the impulse response of discrete filter H and $g(n)=\langle\psi_{-1}(x),\phi(x-n)\rangle$ the impulse response of filter G. With properly chosen $\phi(x)$ (and hence $\psi(x)$), H is corresponding to a low-pass filter and G corresponding to a high-pass filter. Let $\tilde{H}$ with impulse response $\tilde{h}(n)=h(-n)$ be the *mirror filter* of H, and $\tilde{G}$ with