

Detection of microcalcifications in mammograms using local maxima and adaptive wavelet transform analysis

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A method for computer-aided diagnosis of microcalcification clusters in mammogram images is presented. Microcalcification clusters which are an early sign of breast cancer appear as isolated bright spots in mammograms. Therefore they correspond to local maxima of the image. The local maxima of the image is first detected and they are ranked according to a higher-order statistical test performed over the subband domain data.

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Introduction: Microcalcification clusters are an early sign of breast cancer. The survival rate approaches 100 per cent if cancer is detected early. Microcalcifications (MC) appear as isolated bright spots on mammograms images [1-4].

MCs correspond to local maxima of a mammogram as they are relatively bright and tiny regions in the image. The first step of our method is the detection of the local maxima of the mammogram image. Although a typical mammogram is much smoother than most natural images there are thousands of local maxima in a mammogram image. After detecting the maxima locations we rank them according to a higher-order statistical test performed over the subband domain data obtained by the adaptive wavelet transform. The distribution of wavelet data corresponding to the regular breast tissue is almost Gaussian [3, 4]. However, MCs are different in nature than regular breast tissue and they produce outliers in the subband domain. We take advantage of this fact and rank the local maxima according to a higher-order statistical test estimated in the neighbourhood of each local maximum. When the data is Gaussian the test statistics becomes zero. The higher the value of the test, the higher the rank of the maximum. Peaks due to MCs receive high ranks. The maxima due to small variations in the pixel values and smooth edges became low ranks.

We recently developed methods for detection of MCs based on higher-order statistics, and wavelet analysis [3, 4]. In these schemes the subband (or wavelet) domain image $|x_{hh}| + |x_{hl}| + |x_{lh}|$ of the mammogram image x is divided into overlapping small windows and a higher-order statistic (HOS) [5] is estimated in each window. The windows with HOS values higher than a threshold value T are marked as regions containing MC clusters. A weakness of the methods [3, 4] is that the threshold T should be estimated from a set of training images. The threshold has to be adjusted from scanner to scanner and according to the data set. In addition, we compute the HOS test only around maxima locations instead of the entire image, thus achieving a computationally more efficient method than [3, 4]. The HOS test is reviewed later in this Letter.

Another important feature of this Letter is that an adaptive wavelet (subband) transform [6] is used instead of a regular wavelet transform (WT). It is experimentally observed that adaptive WT provides better results than the ordinary Daubechies WT.

Adaptive wavelet transform: Classical adaptive prediction concepts are combined with the perfect reconstruction filter bank theory in [6] where the key idea is to decorrelate the polyphase components of the multichannel structure using an adaptive predictor P as shown in Fig. 1. Adaptation of the predictor coefficients are carried out by a least mean square (LMS)-type algorithm.

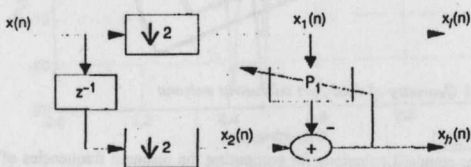


Fig. 1 Analysis stage of two-channel adaptive filter bank structure (P_1 represents an adaptive predictor)

In Fig. 1, $x_1(n)$ is the downsampled version of the original signal, $x(n)$, thus it consists of the even samples of $x(n)$. Similarly, the signal $x_2(n)$ consists of the odd samples. An LMS-based FIR predictor of $x_2(n)$ from $x_1(n)$ can be expressed as $\hat{x}_2(n) = \mathbf{w}(n)\mathbf{x}_1^T(n)$ where $\mathbf{x}_1(n) = [x_1(n-L), \dots, x_1(n+L)]^T$ is the observation vector, and the $2L+1$ vector $\mathbf{w}(n)$ is the vector of predictor coefficients which is adapted by the equation

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \frac{\mathbf{x}_1(n)e(n)}{\|\mathbf{x}_1(n)\|^2} \quad (1)$$

where the error signal $e(n) = x_2(n) - \hat{x}_2(n)$.

The filterbank structure shown in Fig. 1 is the simplest adaptive wavelet transform (AWT) structure. In this structure, the 'highband signal' is essentially the prediction error and as a result the subsignals are expected to be decorrelated. Other AWT structures with antialiasing filters for the upper branch signal can be found in [6].