

Visualization of mammograms via fusion of enhanced features

Iztok Koren^a, Andrew Laine^b, Suzanne Smith^c, Edward Nickoloff^c, and Fred Taylor^a

^aDepartment of Electrical and Computer Engineering,
University of Florida, Gainesville, FL 32611, USA

^bCenter for Biomedical Engineering,
Columbia University, New York, NY 10027, USA

^cDepartment of Radiology,
Columbia-Presbyterian Medical Center, New York, NY 10032, USA

Image enhancement in mammography is typically concerned with either general visibility of all features or conspicuity of a specific sign of malignancy. We describe a synthesis of the two approaches through fusion of locally enhanced microcalcifications, circumscribed masses, and stellate lesions. Both local processing and image fusion are performed within a single wavelet transform framework which contributes to the computational efficiency of the method. The algorithm not only allows for efficient combination of specific features of importance, but also provides a flexible framework for incorporation of distinct enhancement methods and their independent optimization.

Mammography, contrast enhancement, image fusion, wavelet transform.

1. INTRODUCTION

In general, mammographic image enhancement methods target either visualization of all features in an image [1, 2, 3, 4] or visibility of specific features of importance such as microcalcifications [5].

Methods from the first category are not optimized for a specific type of cancer, and are often developed for a framework more general than mammography alone. The second category approaches can be quite successful in their area of specialization; however, in order to process mammograms for presence of distinct features, independent application of different algorithms could result in both larger number of images to be interpreted by a radiologist and increased computational complexity.

Here, we present an approach which overcomes these shortcomings and problematic limitations via synthesis of the two paradigms by means of image fusion. The algorithm consists of two major steps: (1) wavelet coefficients are modified distinctly for each type of malignancy; (2) the obtained multiple sets of wavelet coefficients are fused into a single

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set from which a reconstruction is computed. The scheme allows efficient deployment of an enhancement strategy appropriate for clinical screening protocols: an enhancement algorithm is first developed for each specific type of feature independently, and the results are then combined using an appropriate fusion strategy.

2. WAVELET TRANSFORM

Wavelet based methods are particularly well suited for processing of mammograms since mammographic features greatly vary in shape and size. Commonly used orthogonal and biorthogonal wavelet transforms, however, may not be the best tool for mammographic image enhancement because their lack of translation invariance can lead to artifacts possibly affecting a radiologist's interpretation. Translation-invariant but overcomplete wavelet representations avoid artifacts and have been successfully used for processing of mammograms [1, 2, 5].

Rotation invariance is another desirable property of wavelet decompositions. The concept of steerability [6] has been utilized for construction of wavelet transforms enabling rotation-invariant processing of mammograms [3]. Our scheme is built around a multiscale spline derivative-based transform which, in addition to being translation-invariant and approximately steerable, is also suitable for non-linear methods of enhancement.

We use x - y separable wavelets

$$\psi(x, y) = \frac{d^d \beta_{p+d}(x)}{dx^d} \beta_{p+d}(y), \quad (1)$$

where $\beta_p(x)$ denotes a central B-spline of order p , and limit ourselves to first and second derivatives $d \in \{1, 2\}$. Figure 1 shows wavelets with $p=3$.

A rotation of wavelet $\psi(x, y)$ by angle θ can be expressed as

$$\psi^\theta(x, y) \simeq \sum_{i=0}^d \binom{d}{i} n_x^{d-i} n_y^i \frac{d^{d-i} \beta_{p+d}(x)}{dx^{d-i}} \frac{d^i \beta_{p+d}(y)}{dy^i},$$

where $\vec{n} = (\cos \theta, \sin \theta) = (n_x, n_y)$. The terms $\frac{d^{d-i} \beta_{p+d}(x)}{dx^{d-i}} \frac{d^i \beta_{p+d}(y)}{dy^i}$ represent basis functions needed to approximately steer wavelet $\psi(x, y)$. A dyadic wavelet transform using these basis functions can be implemented as a filter bank consisting of one-dimensional filters only [7].

3. ENHANCEMENT OF MAMMOGRAPHIC FEATURES

3.1. Microcalcifications

Microcalcifications appear on mammograms in approximately half of breast cancer cases. The assessment of shape, number, and distribution of microcalcifications is important for a radiologist to reach diagnosis. Microcalcifications are smaller than 1 mm in size and can be difficult to locate when they are superimposed on dense breast tissue.

Several techniques have been developed to improve the visibility of microcalcifications [5, 8, 9]. The approach devised by Strickland and Hahn [5] is particularly well suited

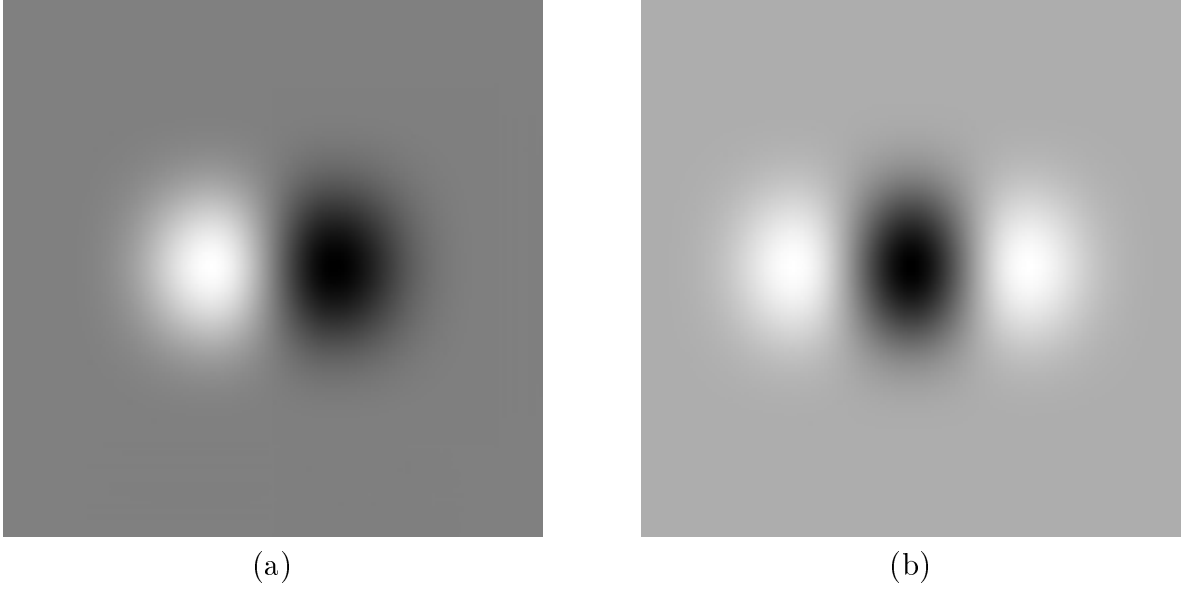


Figure 1. Spline derivatives in the x -axis direction. (a) Wavelet equal to the first derivative of a quartic spline. (b) Wavelet equal to the second derivative of a quintic spline.

for our framework: they used an undecimated wavelet transform to approximate second derivatives of a Gaussian probability density function for a multiscale matched filtering for presence of microcalcifications.

Strickland and Hahn based their method on the observation that the average microcalcification can be modeled by a circularly symmetric Gaussian function. We take advantage of this fact to model microcalcifications by central B-splines. Using B-spline approximations of a Gaussian function, the assumption that a Gaussian object is visible approximately over $\pm\sigma$ pixels [5], and the fact that mammograms in the University of Florida database were digitized at $116\mu\text{m}$ resolution, four levels of the transform described in Section 2 with, for example, $p=3$ are needed to encompass different sizes of microcalcifications. The wavelet decomposition including voices at scales 3 and 6 (corresponding to Strickland and Hahn’s octaves “2.5” and “3.5”) was obtained from relations between central B-splines at integer scales [10].

The wavelet decomposition enables approximations both to the second derivatives of Gaussian along x and y directions and to Laplacian of Gaussian across distinct scales employed by Strickland and Hahn. We proceed in a similar fashion: the two outputs per scale are thresholded independently, all binary results are then combined, a circular region centered at detected pixel locations is next multiplied by a gain, and, finally, the modified transform coefficients are used for image fusion.

3.2. Circumscribed Masses

Almost half of missed cancers appear on mammograms as masses. Perception is a problem particularly for patients with dense fibroglandular patterns. The detection of masses can be especially difficult because of their small size and subtle contrast compared with normal breast structures.

Fan and Laine [2] developed a discrete dyadic wavelet transform based algorithm suitable for enhancement of masses. They constructed an approximation to Laplacian of Gaussian across dyadic scales for an isotropic input to a piecewise linear enhancement function.

An approximation to a Laplacian of Gaussian across dyadic scales is easy to obtain using multiscale spline derivatives from Section 2: basis functions $\frac{d^{d-i}\beta_{p+d}(x)}{dx^{d-i}} \frac{d^i\beta_{p+d}(y)}{dy^i}$ with $d = 2$ and $i \in \{1, 2\}$ approximate the second derivative of a Gaussian function along directions of x and y axis. The appropriate transform coefficient at each dyadic scales are then added and their sum input to the piecewise linear function [2]

$$C(x) = \begin{cases} x - (K - 1)T & \text{if } x < -T \\ Kx & \text{if } |x| \leq T \\ x + (K - 1)T & \text{if } x > T \end{cases}$$

used at each level $m+1$ of the transform separately. Due to the expected size of masses, levels greater than 4 are enhanced more aggressively.

The multiplicative factor obtained as the ratio between the output and input of the enhancement function is next applied to the original wavelet coefficients before fusion and the associated inverse wavelet transform are carried out.

3.3. Stellate Lesions

It is important for radiologists to identify stellate lesions since their presence is a serious indicator of malignancy. Stellate lesions vary in size and subtlety and, in addition, do not have a clear boundary, making them difficult to detect.

In the development of our algorithm, we utilized an observation made by Kegelmeyer *et al.* about the distortion of edge orientation distribution induced by a stellate lesion [11]. Normal mammograms show a roughly radial pattern with structure radiating from the nipple to the chest wall. A stellate lesion not only changes this pattern, but also creates another center from which rays radiate.

The wavelet transform from Section 2 allows directional analysis using approximations to both first and second steerable derivatives of a Gaussian. A multiscale derivative-pair quadratic feature detector was computed by finding the maximum of the local oriented energy with respect to angle θ ,

$$E_{2^m}^\theta(x, y) = \sqrt{(W1_{2^m}^\theta s(x, y))^2 + (W2_{2^m}^\theta s(x, y))^2}, \quad (2)$$

where $W1_{2^m}^\theta s(x, y)$ and $W2_{2^m}^\theta s(x, y)$ denote wavelet decompositions using first (Equation (1) with $d = 1$) and second (Equation (1) with $d = 2$) derivative wavelet, respectively, steered to angle θ . The angle that maximizes the local oriented energy (2) represents orientation at pixel location (x, y) .

Similar to the method from Section 3.1, processing is carried out within windows of scale dependent size: 1-norm of differences between the local and average orientations was computed in the window and used as a measure of orientation nonuniformity. Soft thresholding as a function of the orientation nonuniformity measure was next applied to the transform coefficients at each dyadic scale independently. The altered coefficients are then included for fusion and reconstruction.

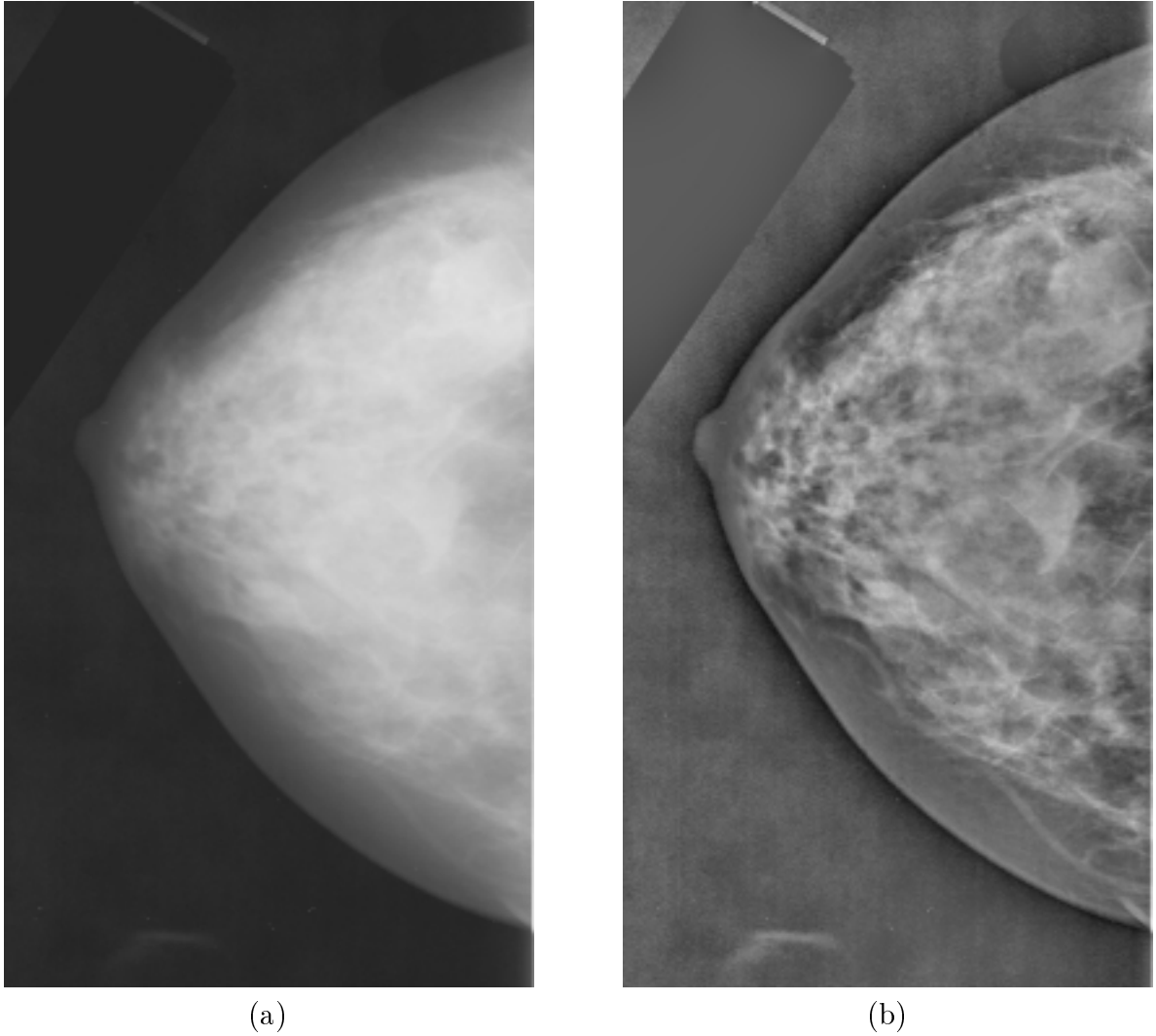


Figure 2. (a) The cranio-caudal view of the left breast. (b) Enhanced image improves visualization of the borders of the mass.

4. FUSION OF ENHANCED FEATURES

After coefficients are processed for enhancement of distinct mammographic features, the corresponding coefficients are combined according to a fusion rule into a new set of transform coefficients from which the fused result is reconstructed. As a fusion rule, the maximum oriented energy criterion was chosen: at each position and scale of the transform, the coefficient with greatest local energy was selected [12].

It is also possible to put distinct weights on selected features, and exclude other features from the final result.

Figure 2 shows the original mammogram and the processed image with improved contrast between the fat and glandular tissue.

5. CONCLUSION

The presented method incorporates a variety of properties of mammographic image enhancement techniques tailored to specific signs of malignancy into a unified computational framework. A multiscale spline derivative-based transform proved flexible enough for implicit enhancement of individual types of mammographic features and thus enabled processing within a single wavelet transform decomposition. In addition to its efficiency, the algorithm is well suited for further refinements; optimizations can be performed for each type of malignancy alone, and separately for the fusion strategy.

Our preliminary experiments imply that an enhancement via fusion approach can provide more obvious clues for radiologists. Further clinical tests are planned to verify that the versatility of this paradigm can provide a better viewing environment for a more reliable interpretation in screening mammography.

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