Enhancement of Mammograms from Oriented Information

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Abstract

Mammograms can depict most of the significant changes of breast disease. The primary radiographic signs of cancer are masses (its density, size, shape, borders), spicular lesions and calcification content. These features may be extracted according to their coherence and orientation and can provide important visual cues for radiologists to locate suspicious areas without generating false positives.

In this paper, an artifact free enhancement algorithm based on overcomplete multiscale wavelet analysis is presented. The novelty of this algorithm lies in its detection of directional features and removal of unwanted perturbations. Compared to existing multiscale enhancement approaches, images processed with this method appear more familiar to radiologists and naturally close to the original mammogram.

1 Introduction

Mammograms can detect tumors that are an eighth of an inch in diameter, while manual examination usually fails to detect tumors smaller than a half-inch. Reliable diagnosis by radiographs of malignant breast disease depends on observing local and distant changes in tissues produced by disease over time. Of the visual signs of cancer found by radiologists, the early signs of masses and calcifications are most important [13] to reduce mortality. Unfortunately, at the early stages of breast cancer, these signs are very subtle and varied in appearance, making diagnosis difficult and challenging even to specialists [5].

Multiscale representations employing wavelet bases have been carried out for mammographic feature analysis [10, 17]. Li *et al.* [11] extended a conventional multiresolution wavelet transform into a multiresolution and multiorientation wavelet transform. Directional wavelet analysis was applied to capture orientation information within each mammogram [9].

Freeman and Adelson [3] first proposed the concept

of steerable filters and applied it to several problems in the area of computer vision. With a set of "basis filters", one can adaptively steer a filter along any orientation. Hilbert transform pairs were constructed to find a local "oriented energy" measure and dominant orientation.

Kass and Witkin [6] developed an algorithm for estimating the orientation of texture patterns. An orientation pattern was decomposed into a flow field, describing the direction of anisotropy, and a residual pattern obtained by structuring the image in a coordinate system built from the flow field. Texture orientation was estimated from Laplacian of Gaussian filters. Rao and Schunck [18] proposed another algorithm based on gradient of the Gaussian. Their algorithm incorporated a more sophisticated scheme for computing coherence of the flow field.

In this paper, an enhancement algorithm based on overcomplete multiscale wavelet analysis is described. These redundant representations provide the property of shift invariance which is useful for analysis of images. Features were extracted by separable steerable filters. A coherent image and phase information were then generated. A nonlinear function, integrating coherent image and phase information, was then applied to the transform coefficients at each level. An enhanced image was obtained via an inverse wavelet transform of the modified coefficients. The novelty and advantage of this algorithm compared to existing techniques lies in its detection of directional features and removal of unwanted perturbations (artifacts).

2 Measure of Coherence

Texture plays an important role in many machine vision and image processing tasks including surface inspection, scene classification, surface orientation and shape determination [2]. Texture patterns may be characterized by extracting measurements that quantify the nature and directions of a pattern. Most

breast carcinomas have the appearance of stellate lesions consisting of a central mass surrounded by radiating spicules. The subtle spicules radiate outwardly in all directions and vary in length. These can provide an important visual cue for early cancer detection.

Much attention has been given to the notion of decomposing an intensity image into intrinsic images to extract significant information [1]. These intrinsic properties represent basic components of the image formation process and therefore can reveal features “hidden” inside an image. The information they provide is beyond the intensity image alone.

Rao and Schunck [18] defined the orientation field of a texture image to consist of two images — an angle image and a coherence image. The angle image denotes the dominant local orientation at each point and the coherence image represents the degree of anisotropy at each point. They strongly advocated the use of angle and coherence images as intrinsic images. In this paper, we investigated the efficiency of these two representations to capture and enhance features of importance to mammography.

3 Methodology

Our algorithm consists of the following four steps.

(1) Overcomplete Multiscale Analysis: Wavelet transforms, owing to their localization characteristics, are powerful tools of analysis for many signal and image processing applications. Multiscale analysis can extract features at distinct scales and make visual local information often less obvious in an original mammogram. A major drawback of traditional wavelet transforms is their lack of translation invariance, making the content of wavelet subbands unstable under the translations of an input signal. In our algorithm, a digitized mammogram was decomposed using a fast wavelet transform algorithm (FWT) [12]. In order to obtain wavelet coefficients at each level without downsampling, a undecimated “*algorithme à trous*” (algorithm with holes) [4, 19] was implemented. In the spatial domain, this redundant representation yields coefficients without aliasing.

(2) Separable Steerable Filters: A filter is called “steerable” if the filter at an arbitrary orientation can be expressed as a linear combination of a set of basis filters, generated from rotations of a single kernel [3]. Steerable filters [3, 8, 7], which can be adaptively adjusted to arbitrary orientation, were used to detect stellate patterns of spicules and locate feature orientations more precisely. As pointed out by Perona [16], the separability property of the filters can speed up computations considerably when convolved with large

image matrices. In our algorithm, we used three basis functions as steerable filters. The x - y separable steerable approximations of filter kernels were generated by Singular Value Decomposition (SVD) [3, 16]. Using a set of separable steerable filters, the magnitude (M^i) and associated dominant directions (A^i) of local energy were determined by the basis functions and their Hilbert transforms [3, 14, 15].

(3) Coherence Maps: A coherence map is an image showing a local measure of the degree of anisotropy of flow [6, 18]. If orientations of a texture pattern at any point (x_i, y_i) are coherent, then magnitude and phase information are important and should be emphasized. Conversely, if the orientations are not coherent, the magnitude and phase information may be neglected or attenuated. Kass and Wilkin [6] suggested a simple way of measuring strength of coherence. An alternative measure of coherence proposed by Rao and Schunck [18] was obtained by weighting the energy with the normalized projection of energy within a specified window ($\mathcal{W}$) onto the central point (j, k) of each window. The coherence (C^i) was expressed as

$$C^i(j, k) = M^i(j, k) \frac{\sum_{(m,n) \in \mathcal{W}} |M^i(m, n) \cos(A^i(j, k) - A^i(m, n))|}{\sum_{(m,n) \in \mathcal{W}} M^i(m, n)}, \quad (1)$$

where $M^i(j, k)$ and $A^i(j, k)$ denote energy and phase of point (j, k) at level i , respectively. This coherence measure incorporates the gradient magnitude and hence places more weight on regions that have higher visual contrast. Experimentally, this method outperformed previous measures applied to similar data [18]. In our algorithm, we implemented this approach to measure each coherence map. In order to capture distinct features at each level, we changed the window size at each level. At the finest level, a 5×5 window was used. While for the coarser levels, larger windows (7×7 , 9×9 , 11×11) were used. For simplicity of implementation, an odd window size was selected at each level. The measure of coherence C^i was computed from Equation (1). The combination of coherence and orientation structures was better able to extract more salient features of spiculated lesions. In overview, a schematic diagram of the processing Steps 1–3 is shown in Figure 1.

(4) Nonlinear Operators: So far, we have computed the information needed in our algorithm. next, a nonlinear operation was applied within each level to precisely modify transform coefficients. This operation integrated both coherence map and phase infor-

Figure 1: Overview of processing.

mation.

A. Modification from Coherence Map: Let $C^i(j, k)$ denote the coherence measure of point (j, k) at some level i . Modifications of coherence (computed in place) were obtained by a nonlinear function expressed as

$$C^i(j, k) = \begin{cases} \log \sqrt{C^i(j, k)}, & \text{if } C^i(j, k) > 1, \\ 0, & \text{otherwise,} \end{cases} \quad (2)$$

such that a coefficient was emphasized if its coherence measure was large and attenuated if small.

B. Modification from Phase: Phase information is important to characterize well an oriented texture. Therefore we did not neglect its contribution in the modification of coefficients. We applied a sinusoidal weighting to the phase information. The “detail” sub-bands of wavelet coefficients obtained in Step 1 included two components: the component along x direction and the component along y direction. The x component was obtained by high-pass filtering along the x direction, hence mostly vertical features within the mammogram were detected. We emphasized the points whose dominant orientations were near 0 and π (with respect to the vertical axis). Thus, the modification from phase information was

$$A^i(j, k) = 0.01 + |\cos(A^i(j, k))|. \quad (3)$$

The y component was obtained by high-pass filtering along the y direction, hence horizontal features of an image were detected. We emphasized the points whose dominant orientations were near $\frac{\pi}{2}$ and $\frac{3\pi}{2}$ (with

respect to the vertical axis). The modification from phase information was

$$A^i(j, k) = 0.01 + |\sin(A^i(j, k))|. \quad (4)$$

The modifications from coherence map and phase at level $i - 1$ were combined to adjust each wavelet coefficient at level i . The final modification was therefore

$$W^i = T^{i-1} \cdot C^{i-1} \cdot A^{i-1} \cdot W^i, \quad (5)$$

where T^i was a constant at each level. These modified coefficients were then reconstructed, via an inverse fast wavelet transform, to enhance the visualization of possible lesions.

4 Experimental Results

Our algorithm was applied to enhance mammograms using oriented information. In order to capture distinct directions of subtle features, steerable filters were used. Several examples of malignant lesions with distinct radiographic signs of cancer were processed to show the effectiveness of our algorithm. Because of the limit of space we only show one of them here. A mammogram (mam004lcc) with a mass tumor is shown in Figure 2. The craniocaudal view of the left breast shown in Figure 2(b) shows an irregular spiculated mass in retroglandular fat. The enhanced version shown in Figure 2(c) better delineates the margins of the mass.

5 Conclusion

An enhancement algorithm relying on overcomplete multiscale analysis and extracting oriented information at each scale of analysis was investigated. The evolution of wavelet coefficients across scales characterized the local shape of irregular structures. Using oriented information to detect features of an image appears to be a promising approach for enhancing complex and subtle structures of the breast. Steerable filters which can be rotated at arbitrary orientations can reliably find visual cues within each spatial-frequency sub-band of an image. “Coherence measure” and “dominant orientation” clearly helped us to discriminate features from complex surrounding tissue typical in mammograms.

Existing and previous multiscale enhancement approaches [10, 9] attempted to enhance an image by detecting edges. Unfortunately, most edge detection algorithms can not distinguish between “authentic” edges and phantom edges. In contrast, this algorithm relied upon a coherence map and phase information which resulted in an enhancement naturally close to

Figure 2: Mammogram with a mass: (a) Original mammogram, (b) ROI image, (c) enhanced ROI image.

the original image. This type of artifact free enhanced image can provide more “obvious” (and familiar) visual cues for radiologists.

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