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Directionlet transform based sharpening and enhancement of mammographic X-ray images

S. Anand [a,*], R. Shantha Selva Kumari [a], S. Jeeva [b], T. Thivya [c]

[a] Department of Electronics and Communication Engineering, Mepco Schlenk Engineering College, Sivakasi, India
[b] Department of Electronics and Communication Engineering, Renganayagi Varatharaj College of Engineering, Sivakasi, India
[c] Department of Information Technology, Sri Vidya College of Engineering and Technology, Virudhunagar, India

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ABSTRACT

Due to difficulty in detecting the low contrast and noisy nature of X-ray mammography images, they have to be enhanced to obtain a clear and good view. Though Sharpening Technique (ST) is used to enhance the contrast, it introduces noise in the enhancement process, and they do not include anisotropic features. This paper proposes a ST, which uses multiscale linear and anisotropic geometrical features obtained from directionlet transform (DT). The newly formulated method that combines multidirectional geometrical information has various tunable parameters and improved noise control by means of multiscale features. The DT that uses skewed and elongated directional basis functions not only captures the point singularities, but also links them into linear structure. The performance of the proposed DT ST is compared with non-linear unsharp masking (NLUSM). While the DT and LoG based sharpened images are given to the input of standard AHE, their performance is improved. Enhancement Measure and structural similarity measure are used to analyze the performance of the proposed method. Though the images are enhanced, the quality of the image is not degraded. As a specific application, the enhanced images are used to detect the microcalcification and spiculated masses in mammograms.

1. Introduction

Early detection of breast cancer is important and mammography is the primary imaging technique for the detection and diagnosis of breast lesions. The primary goal of mammography screening is to detect small, non-palpable cancers in its early stage. Due to poor visibility, low contrast, and noisy nature of mammograms, it is difficult to interpret the pathological changes of the breast. Thus, enhancing the contrast of the images becomes very important while screening mammograms.

The principal objective of enhancement is to improve the subjective quality of an image so that the result is more suitable than the original image for a specific application. However, the subjective quality of an image depends largely on the sharpness and explicitness of edges. The lack of sharpness in human sight strains to achieve a better focus and weak identification of sharp edges is felt as lack of details. Sharpening is an important process in images to increase the contrast between bright and dark regions to bring out boundary features [1,2]. The principal objective of image sharpening is to highlight fine details or to enhance the blurred regions, therefore this filter has 'high emphasis' character in frequency domain. Improving contrast near the edges is the common approach for image sharpening. For that, the scaled edge information is added near the boundaries of objects in an image [3]. Frequently the edge information is determined by high pass (HP) filter and more sensitive to noise and limited directions. Laplacian of Gaussian (LoG) is such an operator, which can able to control the noise influence by adjusting the smooth (or) shape parameter [4] and LoG based unsharp masking (USM) is commonly used ST. However, this smoothing operation weakens the actual gradient and need tradeoff between smoothing parameter and the number of detected edge pixels [5]. The higher level of smoothness of LoG affects the texture regions that are visually important in mammogram images. Moreover, due to isotropic, LoG fails to capture anisotropic features.

In mammogram screening, human visual perception remains the primary approach to extract relevant information [6] such as microcalcification, architectural distortions [7], masses associated with breast cancer [8] etc. However, contrast between malignant tissue and normal dense tissue present on a mammogram may below the threshold of human perception [9]. Our emphasis at this stage is to provide superior enhanced image for screening purpose and aid subsequent application. In the past, several contrast enhancement methods have been proposed [10–13]. Many research works have been presented on mammograms

* Corresponding author. Tel.: +91 98421 49397/4562 235410; fax: +91 4562 235111.
E-mail addresses: ks.an@yahoo.com, sanand@mepcoeng.ac.in (S. Anand).

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for its contrast enhancement and for identification of image features [13–19]. Kim et al. proposed a method for mammographic image enhancement using first derivative and local statistics [20]. The Contrast Limited Adaptive Histogram Equalization (CLAHE) introduced by Zuiderveld has given very good results in the case of image contrast enhancement [21], but it is not suitable for mammogram images contains of very fine details. In addition to common enhancement algorithms, wavelet based enhancement algorithms are also found in literature [22–25]. Though image processing in wavelet domain is popular, isotropic and limited directivity are main drawbacks. Therefore, anisotropic transforms are introduced in many image-processing applications. Medical imaging field also found some applications using anisotropic transform such as curvelets [26,27], contourlets [28,29]. Directionlet transform is one such anisotropic transform and their significances of applications are discussed in [30–32]. A non-linear USM (NLUSM) technique also introduced for mammogram image enhancement [33]. Although, varieties of contrast enhancement algorithms are present in the literature, dealing with images having fine details such as mammogram is still a research issue. Therefore, this paper focuses on mammogram image enhancement by sharpening method using directionlet anisotropic features.

The main contributions of this work are

- ST that uses multidirection multiscale anisotropic features provided by DT. This algorithm combines the DT coefficients in a new way and sharpens the mammogram images in selective regions, and controls the noise effect using scale multiplication.
- The sharpened images are given as the input to AHE algorithms to avoid the flat handling of textured mammogram thereby improves their performance.
- The enhanced images are applied with simple threshold to detect the microcalcification in mammogram images.

While sharpening the image, the noise also enhanced (i.e.) the invisible noise in the image is amplified and texture in areas that looked smooth in the original images. Depending upon the local image variance, the algorithm discriminates the homogeneous and non-homogeneous regions and the algorithm is applied. In addition, the proposed method enhances the edges moderately and avoids unnatural pronounced edges. Being multidirectional, anisotropic characteristics of this algorithm, it preserves the local features than the commonly used enhancement algorithms.

2. Multiscale and multidirection edge extraction

The linear structures such as edges and textures are often most important features in the mammogram images. Image textures do have sharp intensity variations that are often not considered as edges. The discrimination between edges and textures depends on the scale of analysis. While enhancing, suitable importance must be given to both objects and textures present in mammogram images. This has motivated researchers to detect image variations at different scales and directions. Wavelet is an important tool to analyze scale space representation of images. This section explains the extraction of scale space features using isotropic wavelets and anisotropic directionlets.

2.1. Wavelet and edge extraction

The sharpening enhancement intensifies of higher frequency (HF) components that represent the edges of the image. Therefore, the image sharpening largely depends upon edge features. Wavelet transform (WT) is the good choice for effective edge information detection. WT has a collection of functions that are used to decompose signals into various frequency components at an appropriate resolution for a range of spatial scales through directional features. Their coefficients are proportional to the gradient and the modulus of this gradient vector at various scales implies the multi scale edge features. By incorporating the multiscale edge information, noise can be suppressed efficiently. The decomposed wavelet coefficients provide the explicit information on the location and type of the edges in the form of signal singularities and highlight the localized signal structures. Common edge determination algorithm detects points of sharp variation in an image $f(x_1, x_2)$ by calculating the modulus of its gradient vector. The partial derivative of 'f' in the $\mathbf{x} = (x_1, x_2)$ plane is calculated as an inner product with the gradient vector. A multiscale version is implemented by smoothing the surface with a convolution kernel $\theta(x)$ that is dilated. This is computed with two wavelets that are the partial derivatives of $\theta(x)$. $\psi^1 = -\partial\theta/\partial x_1$ and $\psi^2 = -\partial\theta/\partial x_2$. For $1 < k < K$, we denote $\psi_s^k = -\partial\theta/\partial x_1$ for different orientation 'k' with scale $s \in \mathbb{Z}$. Edges and textures are discriminated with 'k' oriented two dimensional wavelet transforms. The wavelet transform of $f(x_1, x_2)$ at $\mathbf{u} = (u_1, u_2)$ is

$$W^k f(\mathbf{u}, s) = \left\langle f(\mathbf{x}), \psi_s^k(\mathbf{x} - \mathbf{u}) \right\rangle = f(\mathbf{x}) * \psi_s^k(\mathbf{u}) \quad (2.1)$$

Eq. (2.1) gives direct intuition that the various oriented wavelet functions $\psi_s^k(\mathbf{u})$ convolved with image $f(x)$ provide the multiscale and multidirectional edge as well as texture information. However, they have limited directions due to separable implementation and fail to capture anisotropic features that are very important in image processing applications.

2.2. Directionlet-skewed, elongated, anisotropic basis functions, and edge extraction

Isotropy and anisotropy are the two types of basis functions to represent the simple image discontinuity along a smooth curve as in Fig. 1. Although, wavelets (isotropic) efficiently represent the point singularities, but fails to achieve the curve like linear structures. However, discontinuity curves present in the images are highly anisotropic and they are characterized by a geometrical coherence. These features are not properly captured by the standard WT that uses isotropic basis functions and they fail to represent the edges and contours effectively. On the other hand anisotropic wavelets (i.e.) contourlets, directionlet etc., are capable to overcome this insufficiency.

DT that has anisotropic skewed and elongated basis functions in various scales efficiently represents the edges. The seven Haar based DT basis functions specified in [30,31] are considered in this paper as shown in Fig. 2. In our scheme, these Haar DT functions are convolved with the mammogram images to obtain the anisotropic features. These DT functions not only provide point singularities but also collect the correlations among point singularities. In addition to anisotropy, multiscale and multidirectional property of DT helps in this sharpening enhancement process of mammogram images. The oriented basis elements give variety of directions, much more than the few directions that are offered by separable wavelets. Anisotropy capture smooth contours in images, the representation should contain basis elements using a variety of elongated shapes with different aspect ratios.

From Eq. (2.1), it is straightforward to express DT as

$$\mathrm{DT}^k f(u, s) = \left\langle f(\mathbf{x}), \varphi_s^k(\mathbf{x} - \mathbf{u}) \right\rangle = f(\mathbf{x}) * \varphi_s^k(\mathbf{u}) \quad (2.2)$$

where $\varphi_s^k(\mathbf{u})$ are the directionlets with directions $k = 1, 2, 3, \ldots$ etc. and scales $s = 0, 1, 2, 3 \ldots$ etc. From the Eq. (2.2), it is easy to understand that the image $f(\mathbf{x})$ convolved with DT $\varphi_s^k(\mathbf{u})$ kernels results directional responses of the image. Due to multidirection and