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The study of medical image enhancement based on curvelet[1]

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Abstract.
BACKGROUND: Breast cancer is a tumor that begins in the breast tissue and is largely identified through X-ray imaging; however, human tissue, illumination, noise and other factors make the image's calcifications and masses unclear, which in turn affects the doctors' identification of lesions and normal tissue through X-ray imaging. Therefore, the rate of misdiagnoses can be reduced through the enhancement of X-ray images that make the images' calcifications and masses more prominent.
OBJECTIVE: Enhancing the breast image would highlight the calcifications and masses.
METHODS: One such way to do so is to use a curvelet that can detect curves and can, therefore, enhance the tumor characteristics. Essentially, existing methods perform a curvelet transform on each sub-image simultaneously; as the curvelet is based on the Radon transform, it involves complex computation and can easily result in difficulties. Based on this information, this article improved the algorithm that detects edges by curvelet and refines edges by wavelet. Simulation experiments using mammography X-ray images are implemented through Matlab.
RESULTS: The results suggest that, after implementation of the improved algorithm, the image's edges and textures are clear, the calcifications are independent, and there is no caking.
CONCLUSIONS: The curvelet method is imporved in efficacy with respect to the wavelet method.

Keywords: Image enhancement, wavelet transform, curvelet transform, multi-resolution analysis

1. Introduction

Image enhancement is one of main contents of image processing [1–3], improving the intelligibility of the image, that is highlighting some features of the image selectively, making it more applicable to specific areas is the main objective of image enhancement. Breast cancer is one of tumor, and it is one of the most prevalent diseases among women. Furthermore, breast cancer's fatality rate has steadily increased; this rate increase is due to a variety of factors: diet, environment, stress and other factors. A critical means of diagnosing breast cancer is through X-ray imaging, the human tissue, illumination, noise and other factors make the calcifications and masses of the image are not clear, affecting the doctors' identification of lesions and normal tissue by X-ray images. For this, if enhance the X-ray images before the doctors' diagnose, prominent the calcifications and masses of the images, that we can reduce the diagnostic difficulties caused by the poor picture clarity effectively, to reduce the rate of misdiagnosis.

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The wavelet method can effectively enhance the calcifications in breast X-ray images, but a cancer diagnosis not only needs calcification information but mass characteristics as well. While the wavelet describes singularity well, it does not produce very good results for lines and curves; therefore, the wavelet transform when applied to tumor characteristics does not result in a good enhancement. Therefore, the curvelet should be incorporated into image enhancement. It can better reflect curves so as to enhance the mass characteristics. This will then eliminate poor image clarity which will in turn make diagnosing breast cancer easier and will reduce the rate of missed diagnosis and misdiagnosis [4–6].

Even worse for breast X-ray images than the wavelet is the ridgelet. The ridgelet describes a straight line well, but its effect is not very good for breast X-ray images. The main reason for this inadequacy is that it cannot reflect the curve well [7–9]; therefore, the ridgelet cannot enhance the bump in breast images, even the calcifications with point singularity. In order to have a good tracking performance for a curve, Candes and Donoho presented the idea of division; the divided pieces of the curve fall within the curve and can be approximated as a straight line. Additionally, the smaller the approximation of the block in a straight line and the smaller the block size, the more approximation in a straight line. If a ridgelet transform is applied for a curve in each piece that can be approximated as a straight line, then there will be good results. The method that splits the curve and then applies a ridgelet transform is called the local ridge wavelet transform.

Similarly for images, there is first a wavelet decomposition. The original image is decomposed into a series of sub-images; then, each sub-image is divided into blocks against their own resolution level. Then, a local ridge wavelet transform is applied to each of the respective sub-blocks. This method is called the curvelet transform. Furthermore, the ability to select different block sizes will, of course, obtain better results.

Simulation experiments of mammography X-ray images are implemented by *Matlab*, the results show that the proposed algorithms have many advantages over other algorithms, such as small computation, the edges and textures of the image are clear after dealing, the calcifications are independent, no caking and large white.

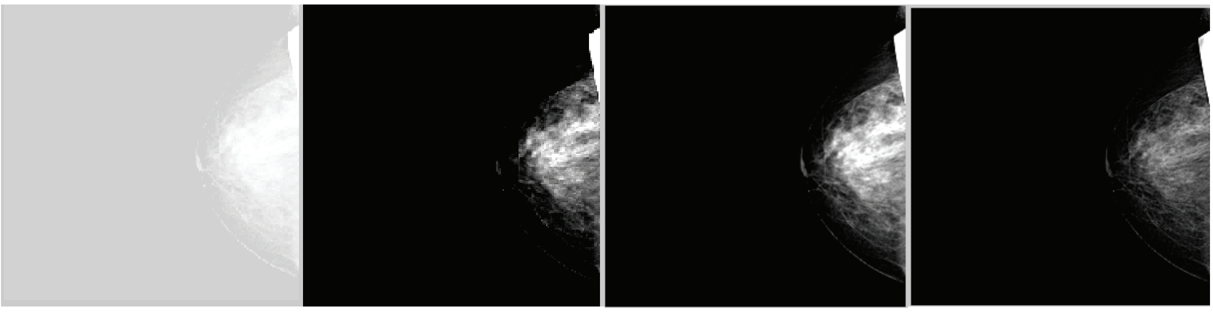
2. Image enhancement algorithm based on curvelet

The curvelet is more suitable for curve tracking than the wavelet; therefore, incorporating the curvelet into imaging will enhance the edge detection of lumps in breast X-ray images. The basic idea can be surmised as: first, the image wavelet decomposition is applied; next, the high-frequency sub-image is enhanced; and then, the edge information of the low-frequency sub-image is extracted with the curvelet transform. The specific process of edge extracting is as follows:

1. First, block all of the low frequency sub-scales. The block size can be different according to different scales. For a small scale, the resolution is high; the block size should be small, leading to more precise details.
2. Next, perform a local ridgelet transform on all the sub-images that have been divided into blocks. The minimum resolution level sub-image first: first, Radon transformation, then the results of the transformed wavelet transform. The final result is de-noised, and the processing is enhanced.

The chunking approach is introduced in the following:

There are two important aspects to consider about block size: first, the smaller the block size, the closer of curve that fell into the blocks in a straight line, meaning that it can more accurately follow the curve; second, if the block size is too small, there will be some accompanying problems, like the block



(a) (b) (c) (d)

Fig. 1. Enhanced images produced by various methods.

effect, in which the computing capacity results in poor results. Generally, the overlapping sub-block approach is used.

In summary, the enhanced algorithm is as follows, set the original image $f(x, y)$:

The first step of $f(x, y)$ is wavelet decomposition.

Second is the high-frequency sub-image processing.

The third step is edge extraction that is performed in two steps. First, each low-frequency sub-image undergoes curvelet transform, and then, the edge information is extracted:

1) Calculate the modulus and phase angle.
2) Search local modulus maxima set of wavelet coefficient from the coarsest resolution level along the $A_{2^j}f(x, y)$ direction, making sure to exclude points at which the modulus value is less than a given threshold.
3) For each j-level edge point, search for points for which the distance is less than a $j + 1$ level, and then insert to points of j level.

The fourth step is edge enhancement.

The fifth step is to perform a curvelet transform on each sub-image, respectively.

The sixth step is wavelet reconstruction.

The seventh step is stretching of the image's gray values.

3. Medical image simulation

The simulation was done on female breast X-ray images given by the Heilongjiang Provincial Tumor Hospital. The image size was $256 * 256$. The chosen wavelet base is the biorthogonal spline wavelet CDF9-7 [7]. The decomposition scale is $J = 3$. The high-frequency sub-image further decomposition scale is $K = 2$. The wavelet base is the $Haar$ wavelet. The gain factor is as follows: $\omega_{31k} = \omega_{32k} = \omega_{33k} = 1.5$, $\omega_{21k} = \omega_{22k} = \omega_{23k} = 1.2$, $\omega_{11k} = \omega_{12k} = \omega_{13k} = 1.1, k = 1, 2, 3, 4$. The block size is $m_1 = 80$, $m_2 = 50$, $m_3 = 30$. The thinning area size is $a = 3$. The simulation results are compared and analyzed with the wavelet nonlinear enhancement method [10], the histogram equalization method and the histogram transformation method [11]. The $db4$ wavelet in chosen in the wavelet nonlinear enhancement method. The threshold is $T_1 = 0$, $T_2 = 0.7$. The gain factor is $k_1 = 0.6$, $k_2 = 2$. The target gray zone for the histogram transformation method was chosen as [0.3,0.7]. The simulation results are shown in the following Fig. 1.

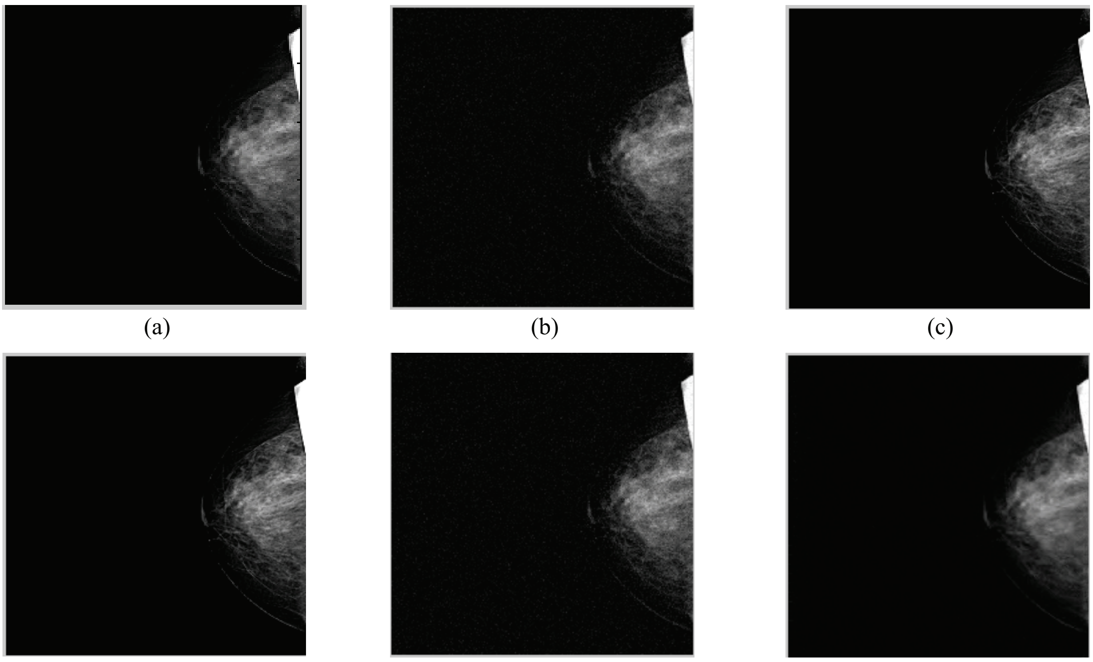
Figure 1(a) is the image resulting from the histogram equalization method, and as can be seen, this method produces a very poor image. Figure 1(b) is the image resulting from the histogram transform

Table 1
Indicators of enhancement result

Method	Mean	MSE	Contrast gain
Histogram equalization	11.3250	10.7915	0.1255
Histogram transformation	11.3891	44.6749	0.9033
Nonlinear wavelet method	12.48451	31.4559	0.9048
This curvelet method	11.3250	32.5333	0.9095

Table 2
Indicators of enhanced images for original image

	Mean	MSE	Contrast gain
Original image	11.3250	32.6635	0.9026
Wavelet method	11.3891	33.1529	0.9082
Curvelet method	11.3250	32.5333	0.9095



(a) (b) (c) (d) (e) (f)

Fig. 2. Comparison between the wavelet method and the curvelet method.

method. Figure 1(c) is the image resulting from the wavelet nonlinear method. This image is clearly better than the previous two methods, but agglomeration exists. Figure 1(d) is the image resulting from this curvelet method. This method has multiple advantages: the edge contour is clear, the calcification is independent and there is no agglomeration. Table 1 details the enhancement indicators for each method.

It is a comparison between the wavelet enhancement method and this curvelet method in Fig. 2. Figure 2(a) is the original image. Figure 2(b) is the noisy image from Fig. 2(a). Figure 2(c) is the enhanced image with the wavelet method applied to the original image. Figure 2(d) is the enhanced image with curvelet method applied to the original image. Figure 2(e) is the enhanced image with the wavelet method applied to the noisy image. Figure 2(f) is the enhanced image with the curvelet method applied to the noisy image.

Figures 2(c) and (d) are the images produced from the wavelet method and the curvelet method, respectively. When comparing these two different images, the detail in the mammary gland portion in Fig. 2(d) is more obvious and detailed than in Fig. 2(c); however, the difference is not great. Figures 2(e) and (f) are the images produced from the wavelet method and this curvelet method on the noisy image. In Fig. 2(e), although it better enhanced than the original noisy image, there is obviously still some grainy noise, and therefore, the noise and calcification are indistinguishable. The noise is substantially

Table 3
Indicators of enhanced images for noisy image indicators of enhanced images for noisy image

	Mean	MSE	Contrast gain	PNSR
Noisy image	11.3320	34.2946	0.9065	90.9607
Wavelet method	11.3287	34.3162	0.9063	96.7076
Curvelet method	11.3002	32.4836	0.9047	100.4242

eliminated in Fig. 2(f), which is the figure that had been treated with the curvelet method. In this figure, the texture detail is clearer than in Fig. 2(e); therefore, the enhancement effect produced by the curvelet method is significantly better than that produced by the wavelet method.

The indicators of the enhanced images for both methods for the original image are listed in Table 2. As shown in Table 2, the mean and variance for the enhanced images resulting from the wavelet and curvelet methods are not very different; however, the contrast gain for the curvelet method is relatively large, so the enhancement effect resulting from the curvelet method is slightly better than the effect produced by the wavelet method.

The indicators of the enhanced images for both methods for the noisy image are listed in Table 3. As shown in Table 3, for the enhanced images produced from the wavelet and curvelet methods on the noisy image, both the mean gray value and contrast gain is decreasing. The last column is the peak signal to noise ratio; the curvelet method's SNR is the largest, which illustrates that the curvelet method's effect is significantly better than the wavelet image's effect on the noisy image.

4. Conclusion

This paper presents a new enhancement method that is based on the curvelet. The results reveal that the curvelet method works better than the wavelet method for an image with no noise or very little noise, but the enhancement is not obvious. However, for images containing more noise, the curvelet method is clearly better than the wavelet method.

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