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Technical Note

Wavelet and fast bilateral filter based de-speckling method for medical ultrasound images

Ju Zhang[a], Guangkuo Lin[a], Lili Wu[a], Chen Wang[a], Yun Cheng[b,*]

[a] College of Information Engineering, Zhejiang University of Technology, Hangzhou 310023, China
[b] Department of Ultrasound, Zhejiang Hospital, Hangzhou 310013, China

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ABSTRACT

Speckle noise is an undesirable part of the ultrasound imaging process, since it can degrade the quality of ultrasound images and restrict the development of automatic diagnostic techniques for ultrasound images. Aiming at the problem of speckle noise, an improved de-speckling method for medical ultrasound images is proposed, which is based on the wavelet transformation and fast bilateral filter. According to the statistical properties of medical ultrasound image in the wavelet domain, an improved wavelet threshold function based on the universal wavelet threshold function is considered. The wavelet coefficients of noise-free signal and speckle noise are modeled as generalized Laplace distribution and Gaussian distribution, respectively. The Bayesian maximum a posteriori estimation is applied to obtain a new wavelet shrinkage algorithm. High-pass component speckle noise in the wavelet domain of ultrasound images is suppressed by the new shrinkage algorithm. Additionally, the coefficients of the low frequency signal in the wavelet domain are filtered by the fast bilateral filter, since the low-pass component of ultrasound images also contains some speckle noise. Compared with other de-speckling methods, experiments show that the proposed method has improved de-speckling performance for medical ultrasound images. It not only has better reduction performance than other methods but also can preserve image details such as the edge of lesions.

1. Introduction

Ultrasonic imaging, CT, MRI and other imaging techniques have been widely used in clinical diagnosis. Ultrasound imaging technology is safer than other imaging techniques because it is non-invasive, non-radioactive, convenient and efficient. Therefore, the clinical application of ultrasonic imaging technology has become more important, especially in observing the growth status of the fetus in pregnant women and diagnosis of lesions of the abdominal organs.

However, the existence of speckle noise has degraded the quality of ultrasound images and restricted the development of automatic diagnostic techniques, especially for ultrasound breast imaging. Every year about 500,000 women die from breast cancer partially due to the lack of clear breast ultrasound images. Speckle noise is an undesirable part of the ultrasound image, which masks the small difference in gray level and degrades the image quality. Speckle noise results from a random scattering phenomenon in imaging cell resolution. Therefore, de-speckling is an important step before the analysis and processing of ultrasound images, and many researchers are attracted to devote their efforts to this issue.

According to principles of ultrasonic imaging, the ultrasonic envelope signal received by the ultrasonic imaging system is modeled as a multiplicative model of signal and noise, where the multiplicative noise is speckle noise. On the basis of signal-to-noise ratio (SNR), multiplicative noise in the spatial domain can be modeled by Rayleigh distribution [1], Rician distribution [2], *K* distribution [3], etc. In order to improve terminal display on most ultrasonic imaging instruments, the ultrasonic envelope signal is compressed with logarithmic transformation. After the logarithmic transformation, an improved medical ultrasonic image remains. Additionally, after the logarithmic transformation, the multiplicative noise model is converted to an additive noise model, where the noise can be simplified as Gaussian white noise. Then the 2-D discrete wavelet transformation (DWT) is applied for the log-transformed image. Because wavelet transformation is a linear transform processing, the noise coefficients in the wavelet domain

* Corresponding author. Tel.: +86 13221807158.
E-mail addresses: zjk@zjut.edu.cn (J. Zhang), chengyun.zjhospital@gmail.com (Y. Cheng).

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are modeled by zero-mean Gaussian distribution and wavelet coefficients of the log-transformed noise-free ultrasound image are modeled by generalized Laplacian distribution [4].

In recent decades, several image filtering techniques had been proposed to reduce speckle noise. These de-speckling filters are classified into five categories [5]: local adaptive filters, anisotropic diffusion filters, multi-scale filters, nonlocal means filters and hybrid filters. Commonly used adaptive filters (Lee [6], Frost [7] and SRBF [8]) assume that speckle noise is essentially multiplicative noise. Anisotropic diffusion filters include DPAD [9], SUSAN_AD [10] and OSRAD [11]. Nonlocal means filters are novel de-noising algorithms, such as OBNLM [5], PPB [12] and Guo [13]. For multi-scale filters (wavelet soft/hard threshold's filter [14] and Andria [15]), the wavelet transformation is usually used as a tool to analyze and process the image. Hybrid filters are the combination of several methods. For example, the SAR-BM3-D's filter [16] is the combination of a multi-scale filter with a nonlocal means filter. Wavelet theory has been widely used in image processing due to the advantages of time–frequency analysis and multi-scale analysis. The wavelet de-noising method is better than others in the processing of additive noise, and this method has higher efficiency, which can satisfy general product demand. However, using the wavelet transformation de-noising method to suppress speckle noise of medical ultrasonic images usually cannot get desirable results, because the low-pass component also contains some speckle noise.

In this paper, a novel de-speckling method based on wavelet transformation and bilateral filter is proposed for medical ultrasound images. The bilateral filter not only has better speckle reduction performances but also can preserve image edge details. To improve efficiency and to shorten running time, a fast bilateral filter based on FFT [18] is adopted in this paper.

Therefore, advantages of the wavelet de-noising method and the fast bilateral filter will be combined in this paper. The main idea of our proposed method is as follows: On the basis of the traditional wavelet de-noising method, an improved wavelet threshold function and a new shrinkage algorithm are suggested according to the statistical properties of speckle noise in wavelet domain medical ultrasound images. This new method can effectively suppress the speckle noise in high-pass component. Speckle noise in the low-pass approximation component of medical ultrasound images in the wavelet domain is filtered by the fast bilateral filter. The proposed method not only guarantees speckle reduction but also can greatly shorten running time.

2. The model of medical ultrasound image

Assuming that insonification and the resulting echo signal absorption have sufficiently obtained appropriate dynamic compensation from the ultrasound imaging system, the final ultrasonic envelope signal obtained consists of two parts: the reflected signal of the human body, which is a useful signal, and the noise itself, which is made up of two components, multiplicative noise and additive noise. Multiplicative noise is associated with the principle of ultrasonic signal imaging, which results from a random scattering phenomenon in imaging cell resolution. Additive noise can be considered system noise, such as sensor noise [17]. The ultrasonic envelope signal $f^{pre}(i,j)$ is modeled as follows:

$$f^{pre}(i,j) = g^{pre}(i,j)n^{pre}(i,j) + w^{pre}(i,j), \quad (1)$$

where $(i, j) \in Z^2$ is the two-dimensional spatial coordinates, and the superscript *pre* is the preliminary signal obtained by system. $g^{pre}(i,j)$ and $f^{pre}(i,j)$ denote the original signal and the observed signal, respectively. $n^{pre}(i,j)$ and $w^{pre}(i,j)$ represent the multiplicative and additive components of the noise, respectively, where the $n^{pre}(i,j)$ is the main component of noise.

The effect of additive noise $w^{pre}(i,j)$ on the qualities of the medical ultrasound images is less significant than the multiplicative noise $n^{pre}(i,j)$, and in order to simplify the model (1), the additive noise $w^{pre}(i,j)$ is generally omitted and the following model is obtained

$$f^{pre}(i,j) = g^{pre}(i,j)n^{pre}(i,j), \quad (i,j) \in Z^2. \quad (2)$$

Due to the limited dynamic range of commercial display monitors, ultrasound imaging systems compress the envelope signal with logarithmic transformation to fit in the display range [14]. Logarithmic amplification converts the model (2) into the classical additive noise model as follows:

$$\log(f^{pre}(i,j)) = \log(g^{pre}(i,j)) + \log(n^{pre}(i,j)), \quad (3)$$

where the signal $\log(f^{pre}(i,j))$ is the common medical ultrasonic image.

Since wavelet transformation is a linear transformation, the following model is obtained after two-dimensional discrete wavelet transformation for model (3):

$$W^j_{l,k}(f) = W^j_{l,k}(g) + W^j_{l,k}(n), \quad (4)$$

where $j = 1, 2, \ldots, J, l, k \in Z^2$. $W^j_{l,k}(f)$, $W^j_{l,k}(g)$ and $W^j_{l,k}(n)$ represent the wavelet coefficients of noisy images, noise-free images and speckle noise, respectively. The superscript j represents the decomposition layers of wavelet transformation, and the subscripts (l, k) are wavelet domain coordinates. J denotes the largest decomposition layers. In order to facilitate the representation, we can rewrite (4) as:

$$F^j_{l,k} = G^j_{l,k} + N^j_{l,k}. \quad (5)$$

Since the Bayesian maximum a posteriori estimation will be used to develop a new wavelet shrinkage algorithm in this paper, and since the prior probability of noise-free signal and speckle noise is the premise of using the Bayesian maximum a posteriori estimation, we consider that the wavelet coefficients of noise-free signal will obey the generalized Laplacian distribution [4], and the wavelet coefficients of speckle noise will obey zero mean Gaussian distribution.

The wavelet coefficients of noise-free signal $G^j_{l,k}$ obey the generalized Laplacian distribution, and the probability distribution is:

$$p_G(g) = \frac{\nu}{2s\Gamma(1/\nu)} \exp\left(-\left|\frac{g}{s}\right|^{\nu}\right), \quad s, \nu > 0, \quad (6)$$

where $\Gamma(a) = \int_0^\infty x^{a-1} \exp(-x)\,dx$ represents Gamma function, s is scale parameter, and ν is shape parameter. When ν is selected as 1, formula (6) becomes the Laplacian distribution, which is a special model of generalized Laplacian distribution.

The wavelet coefficients of speckle noise $N^j_{l,k}$ obey zero mean Gaussian distribution

$$p_N(n) = \frac{1}{\sqrt{2\pi}\sigma_N} \exp\left(-\frac{n^2}{2\sigma_N^2}\right), \quad (7)$$

where σ_N denotes the standard deviation of noise in wavelet domain.

3. An improved de-speckling method based on wavelet shrinkage algorithm and fast bilateral filter

On the basis of the traditional wavelet de-noising method, three contributions are made and an improved de-speckling method based on the wavelet shrinkage algorithm with fast bilateral filter is proposed.