

A SPECKLE SUPPRESSION METHOD BASED ON NONLINEAR THRESHOLD WAVELET PACKET IN ULTRASOUND IMAGES

LI Bin ZHUANG Tian-Ge

(Department of Biomedical Engineering, Shanghai Jiaotong University, Shanghai 200030, China)

Abstract A novel method based on nonlinear threshold wavelet packet was explored in order to suppress the speckles in B-scan 3-D ultrasound imaging. Firstly, an original image was separated into two parts by adaptive pre-filtering. These two parts were then transformed into a multiscale wavelet packet (WP) domain and the WP coefficients were processed by a soft thresholding filter method. The processed coefficients for each part were then transformed back into the space domain. Finally, the de-noised image was obtained as the sum of the two processed parts. Performance of this new method has been tested by a computer-simulated image. Ultrasound images set of a plastic bowl in a water tank has been utilized for 3-D ultrasound reconstruction. It was found that this technique reduces the speckle noise effectively, and preserves the resolvable details.

Key words multiscale resolution thresholding, ultrasound (US) speckle, wavelet packet (WP) transform, adaptive weighted median filter (AWMF)

一种基于非线性阈值小波包的超声图像闪斑抑制方法

李斌 庄天戈

(上海交通大学生物医学工程系, 上海, 200030)

摘要 在B超三维成像中,采用了一种新的基于非线性阈值小波包的闪斑(Speckle)噪声抑制方法来提高成像质量。首先将一幅原始图像经过预滤波分解为高频噪声图像和低频主体图像两部分,然后分别经过多分辨率小波包处理,得到一组小波包域的系数,该系数采用一种软阈值滤波算法处理,去除掉其中的噪声并保留下各自的有用信息。两组分别去噪后的小波包系数经反变换回到时域并相加,得到消除了噪声的图像。该算法的性能在计算机仿真图像上进行了验证。采用该方法处理了一组水槽中的碗状物体的B超图像,并进行了三维体视化重构。实验表明,这种方法可以有效地抑制超声闪斑噪声并在重构中保留对象的细节特征。

关键词 多分辨率阈值,超声闪斑噪声,小波包变换,自适应权重滤波器

Introduction

Volume rendering methods are difficult to be used in ultrasound imaging system because of the speckle noise and other limiting. Speckle is a term used for the granular pattern that appears in B-scan images, and can be considered as a kind of multiplicative noise^[1]. It is caused by the constructive and destructive interference of back-scattered signals due to unresolved tissues in homogeneity. It significantly degrades the image quality and in-

creases the difficulty in resolving fine details in images during diagnostic examinations. A major concern in volume rendering is to render the boundaries between different tissues. Boundaries can be detected by computing local gradients in the volume, but these computations will generally be very noise-sensitive.

To deal with noise reduction, a nonlinear threshold wavelet packet (WP) method based on an adaptive pre-filtering for ultrasonic speckle suppression is presented. This method combines the

WP multiscale nonlinear threshold with the AWMF^[3]. After adaptive pre-filtering, both the outputs of the filter and the usually discarded part are processed by the presented method to extract the useful signals. For the purpose of suppressing most part of noise and reserving the most significant features, an optimal threshold depending on the estimation of signal and noise energy levels has been applied to ultrasound image. In this work, we demonstrate that significant enhancement of 3-D ultrasound image reconstruction quality can be achieved when applying the optimal threshold method to a sequential 2-D image set. Performance of this new method has been tested by a computer-simulated image and an ultrasound image set of a plastic bowl in a water tank. It is found that this method can effectively reduce the speckle noise within homogeneous tissue, preserve and enhance details. Thus it improves the robustness of volume rendering in ultrasound imaging.

1 Approaches of Image Processing

The most common noise model for ultrasound image is additive Gaussian noise. But Loupas *et al.*^[1] found that the envelope-detected echo signal with fully developed speckle has a Rayleigh distribution whose mean is proportional to the local variance. Therefore, a noise model can be used for signal processing

$$y_i = s_i + n_i \cdot \sqrt{s_i}, \quad i \in [1, N], \quad (1)$$

where y_i , s_i , and n_i represent, respectively, the observed signal, noise-free signal, and zero-mean Gaussian noise of the i th sample, and N is the number of samples.

First, the original image f is separated into two parts \hat{s}_1 and \hat{s}_2 . Image \hat{s}_1 is the output of the AWMF and image \hat{s}_2 is obtained by subtracting \hat{s}_1 from the original image f . While \hat{s}_1 represents most of the signal, \hat{s}_2 contains most of the noise. Both parts are composed of signal and noise. The two parts are then decomposed into different parts by a 2-D WP transform. The WP coefficients are then processed with the nonlinear threshold

method. We use different thresholds in different scales. These thresholds are acquired according to a nonlinear threshold method. Considering the different proportion of noise in different parts, a noise reduction factor is introduced to modify the threshold in part one.

After soft thresholding, the WP coefficients of the two parts \hat{s}_1 and \hat{s}_2 , are inversely transformed to space domain yielding $f_{\hat{s}_1}$ and $f_{\hat{s}_2}$. These two images represent the signal components extracted from \hat{s}_1 and \hat{s}_2 . The final noise-reduced image is obtained by summing $f_{\hat{s}_1}$ and $f_{\hat{s}_2}$.

2 Adaptive Pre-filtering

The median filter takes the median value of the pixels in its windows as the value of the central point. The number of pixels in the windows must be odd, but the shape of the window is not restricted. In 2-D case, the square-shaped median filter has no preference to the edge direction in vertical or in horizontal edges. It is suitable for ultrasound images since the edges in US images may exist in all directions. In our experiments the 7×7 square window is used.

The weighted median filter extends the simple concept of the median filter by the introduction of weight coefficients. This operation is performed by multiplying each term of the ranked pixel intensity values, $\{f_1, f_2, \dots, f_N\}$, by its respective weight, denoted by w_1, w_2, \dots, w_N , to form an extended sequence $\{w_1 f_1, w_2 f_2, \dots, w_N f_N\}$. For a square window with sides of length $2K+1$, the weight coefficient $w_{i,j}$ at point (i, j) in the window is

$$w_{i,j} = [W_{i,K+1,K+1} - cd\sigma^2/\bar{x}], \quad (2)$$

where $W_{i,K+1,K+1}$ is the central weight and the square brackets denote the nearest integer to the term inside the brackets or zero if the result of the addition within them is negative; c is a scaling constant and d is the distance of the point from the center of the window. The local mean is denoted by \bar{x} and the local variance by σ^2 .

In the adaptive mean-based filter the measure of similarity, p , given by the ratio of local variance over the local mean, is used to control a constant k

for $0 \leq k \leq 1$ by

$$k = (gp - \bar{p}) / p, \quad (3)$$

where \bar{p} is the mean value of p for a local area of an image that is considered to consist of fully developed speckle. The constant g is a scaling factor that ensures k is always less than one. k adaptively changes the output \hat{x} between the original value (x) and the local mean (\bar{x})

$$\hat{x} = \bar{x} - k(x - \bar{x}). \quad (4)$$

The original image is nonlinearly separated into two parts \hat{s}_1 and \hat{s}_2 by using AWMF

$$\hat{s} = f * w \quad (5)$$

$$\hat{s}_2 = \begin{cases} f - \hat{s}_1 & f - \hat{s}_1 \geq 0 \\ 0 & f - \hat{s}_1 < 0 \end{cases} \quad (6)$$

Where f is the original image and w is the impulse response of the adaptive filter.

3 Nonlinear Threshold Wavelet Packet Filtering

The AWMF effectively suppresses speckle. However, it loses much useful detail because it is merely a low-pass filter. When speckle suppression is used, it should be noted that both discarded and retained outputs must be the functions of both signal and noise, while a different part has a different SNR (signal-to-noise ratio). Soft threshold is a multiscale analysis method and it can be used to detect fine details in ultrasonic images. However,

the thresholds in this method are usually determined by the noise level, which is not known a priori and may be difficult to estimate.

X. Hao *et al.*^[23] introduced wavelet multiscale soft threshold method to reduce the speckle of US image, which was pre-filtered by AWMF. But 2-D wavelet transform only separates low frequency coefficients into two parts, a new low-pass coefficient and a high-pass coefficient. The error information between the continued low-pass components will be obtained by the high-pass components, and it will not be decomposed. We use wavelet packet transform. Both the low-pass subband and the high-pass subband can be recursively decomposed by using a pair of wavelet filters, and the entire WP tree can be obtained. Thus we can analyze the local signal more accurately.

The WP filtering method attempts to reject noise by thresholding in the wavelet domain and it has been proved to work well in many applications.

Since the noise variance is not known in practice, it must be estimated from the data. The estimated noise variance is taken to be the standard deviation of the high part of the first level of the wavelet decomposition. Our goal is to optimize the mean-squared error (MSE) $\frac{1}{n} E [\| \hat{s} - s \|^2]$, where σ is the noise level, s is the unknown signal

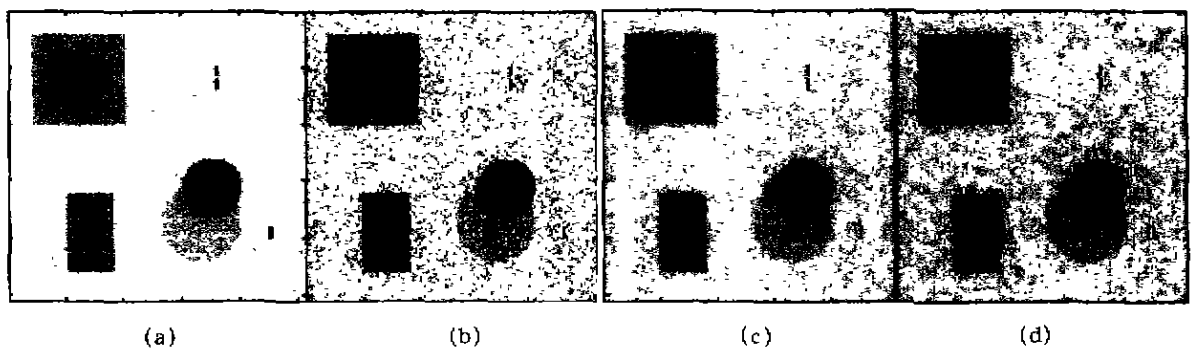


Fig. 1 Suppression of speckles in computer-simulated image
(a) the original image (b) the speckle-polluted image
(c) the noise-reduced image by linear threshold method
(d) the noise-reduced image by multiscale nonlinear threshold wavelet packet method

图 1 去除计算机仿真图像中的闪斑噪声说明
(a)原图像 (b)被闪斑噪声污染的图像 (c)采用线性域值方法去除噪声后的图像
(d)采用非线性域值小波包方法去除噪声后的图像

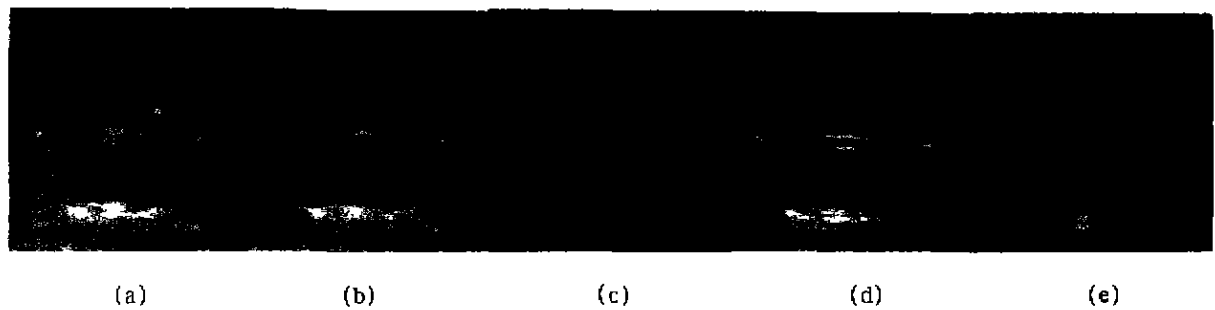


Fig. 2 The ultrasound image of plastic bowl
 (a) original ultrasound image (b) image processed by pre-filtering, which contains most of the signal
 (c) image processed by pre-filtering, which contains most of the noise
 (d) the noise-reduced image processed by the authors' combined filtering method
 (e) the 3-D image of a plastic bowl reconstruction with 98 slices after speckle suppression

图 2 碗状物体的超声图像

(a)原始超声图像 (b)经预滤波后包含主要信号的图像
 (c)经滤波后包含大部分噪声的图像 (d)采用本文方法减少噪声后的图像
 (e)采用 98 片抑制闪斑后的超声图像叠加重构而成的碗状物体的三维图像

from noise data and \hat{s} is the estimate of s . The WP threshold method has three steps:

Step 1. computing the DWP of the noise data, and obtaining the WP coefficients.

Step 2. applying the soft-threshold nonlinearity

$$\lambda t(\nu) = \begin{cases} \nu - t & \nu > t \\ 0 & -t \leq \nu \leq t \\ \nu + t & \nu < -t \end{cases} \quad (7)$$

to the wavelet coefficients with a specially-chosen threshold $t = t_n = \sqrt{\log(n)\sigma}$.

Step 3. performing the inverse DWP on the thresholded wavelet coefficients, and recovering the estimate \hat{s} .

4 Conclusion

Performance of this new method has been tested by a computer-simulated image (Fig. 1). The result shows that the presented method can obtain better results than linear threshold methods. This paper has explored the application of combined filtering of AWMF and soft thresholding wavelet packet method in a volume rendering plas-

tic bowl of ultrasound images (Fig. 2). In this method, different thresholds are employed in different scales, so the resolution of signal and speckle can be obtained more accurately in each scale. The summing of the signal component in the two parts conserves the real signal as more as possible. Distinct features of 3-D reconstructed object have been obtained successfully by applying the method to 98 sequential ultrasound slice images.

REFERENCES

- [1] Loupas T, Meddick W N, Allan P L. An adaptive weighted median filter for speckle suppression in medical ultrasonic images. *IEEE Trans. Circuits Syst.*, 1989, **36** (1): 129-135
- [2] Hao X, Gao S, Gao X. A novel multiscale nonlinear thresholding method for ultrasonic speckle suppressing. *IEEE Trans. Med. Imag.*, 1999, **18** (9): 787-794
- [3] Karaman M, Kutay M A, Bozdagi G. An adaptive speckle suppression filter for medical ultrasonic imaging. *IEEE Trans. Med. Imag.*, 1995, **14** (2): 283-292
- [4] Donoho D L. De-noising by soft-thresholding. *IEEE Trans. Inform. Theory*, 1995, **41** (3): 613-627
- [5] Evans A N, Nixon M S. Speckle filtering in ultrasound images for feature extraction. *Digest of IEE Acoustic Sensing and Imaging Conference*, 1993: 44-49