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An adaptive threshold filter for ultrasound signal rejection

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ABSTRACT

The threshold filter is a frequently used technique in ultrasound B-scan to reject the small echoes contributed from backscattering that blur the tissue interface and reduce the image contrast. Note that using the threshold based on one value would simultaneously destroy local waveform features of the reflection echoes with amplitudes larger than threshold value. To resolve this problem, we developed an adaptive threshold filter based on the noise-assisted empirical mode decomposition (EMD). Computer simulations at 7.5 MHz using a single-element transducer with a bandwidth of 60% and a pulselength of 0.5 μ s were carried out to explore the feasibility of the algorithm. Image measurements on the carotid artery using a 7.5 MHz, 128 elements, 1D linear array transducer with the same characteristics as those in simulations were used to verify the performance of the algorithm in practice. Compared to the result from the conventional threshold technique, the adaptive threshold filter is able to successfully suppress the smaller backscattering signals without changing the local waveform features of the preserved significant echoes due to reflection.

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1. Introduction

Ultrasound B-scan image is a widely used clinical tool for the noninvasive examination of tissue structures. The image brightness is determined by the strengths of echoes produced by changes in the acoustic impedance of tissues. It should be noted that the small signals contributed from the constructive and destructive coherent summation of ultrasound backscattering echoes affect the image quality to some degree, because they form the so-called speckle, which blur the tissue interface to degrade the image contrast [1]. Considering that the small backscattering signals have no useful information to describe the tissue interface, sometimes it is desirable to reject them to make the tissue interface in the B-scan clear.

Among all methods used for signal rejection, the threshold filter based on one value is a simplest approach to remove the small echoes [2,3]. Most commercial ultrasound image systems allow the threshold value to be adjustable in a range from 0 to 2^N (N is the bit number of the digitizer). This design allow users to adjust the image quality by rejecting some gray levels that are useless to structure monitoring. The threshold technique is also used in other medical image process, such as the nuclear medicine imaging [4]. However, it can be expected that using the threshold for signal

rejection would simultaneously change the local waveform features of the preserved echoes larger than threshold value. This is unfavorable to quantitative analysis of ultrasound image based on certain statistical models, such as K and Nakagami statistical models [5,6]. Recall that the statistical models are typically used to describe the signal statistics for the goal of tissue characterization. The statistical distribution of amplitude is a typical statistical property of ultrasound signal. Because thresholding would cause the change in the statistical distribution of ultrasonic signals, the statistical models may not fit the signal statistics well for tissue characterization.

In this study, we developed a new threshold method: an adaptive threshold filter based on the empirical mode decomposition (EMD). 'Adaptive' here means that the threshold filter can work and does not affect local waveform features. The algorithm of this new method consists of two steps: first, it adds artificial white noise to the ultrasonic radio-frequency (RF) data and next, it applies EMD to the noisy RF data. We found that the proposed method is able to reject the small signals from backscattering. More importantly, it does not change the waveform features of the preserved significant echoes due to reflection. This paper is organized as follows: Section 2 introduces the theoretical background. Section 3 shows the methods, including algorithm design, simulations, and experiments. Section 4 describes the results obtained from computer simulations and image measurements on the carotid artery for validating the algorithm and the performance in practice. Section 5 shows the concluding remarks.

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2. Theoretical background

Empirical mode decomposition (EMD) is the key part of Hilbert–Huang transform (HHT) proposed as an adaptive time–frequency analysis method for nonlinear and nonstationary data [7,8]. EMD was developed with the aim of meaningfully determining the instantaneous frequency of a signal. Mathematically, the instantaneous frequency of a signal may be defined using the Hilbert transform. Hilbert transform $Y(t)$ of an arbitrary time series $X(t)$ is given by

$$Y(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{X(t')}{t - t'} dt'. \quad (1)$$

With this definition, $X(t)$ and $Y(t)$ form a complex conjugate pair, and therefore analytic signal $Z(t)$ can be defined as

$$Z(t) = X(t) + iY(t) = a(t)e^{i\theta(t)}, \quad (2)$$

where

$$a(t) = [X(t) + Y(t)]^{1/2}, \quad (3)$$

and

$$\theta(t) = \arctan\left(\frac{Y(t)}{X(t)}\right). \quad (4)$$

The instantaneous frequency can then be defined as

$$\omega(t) = \frac{d\theta(t)}{dt}. \quad (5)$$

The definition in Eq. (5) requires some limitations to be applied to the input data. First, the instantaneous frequency has a single value at any given time, and hence can only describe monocomponent data. Because there is no precise definition of a monocomponent, the narrowband consideration was adopted as a limitation on the data for the instantaneous frequency to make sense. Second, for any function to have a meaningful instantaneous frequency, the real part of its Fourier transform has to comprise only positive frequency components. However, this is a global restriction that may not be useful for nonstationary data, and hence this restriction should be modified from a global one to a local one.

In order to satisfy the above two restrictions, Huang et al. defined a class of functions called intrinsic mode functions (IMFs) for which the instantaneous frequency can be defined anywhere [7]. Actually, the IMF is a single-component signal that fulfills the following conditions: (1) the number of zero and extreme crossings must be no more than one in the entire data set, and (2) the mean value of the up and down envelopes, which are defined using local maxima and minima, respectively, is zero at any time (this means that two envelope curves are symmetrically about the time axis). Huang et al. further developed the EMD method to decompose a signal into a set of IMFs for calculating their instantaneous frequencies using the Hilbert transform [7]. This is the so-called HHT (i.e., the Hilbert transform of IMFs obtained by EMD for time–frequency analysis). The EMD algorithm is explained below.

We first find the local maxima and minima of signal $x(t)$, and use cubic spline interpolation [7] to obtain its up and down envelopes. If the mean of two envelopes is $d_1(t)$, the difference between the signal and $d_1(t)$ is the first component $h_1(t)$

$$h_1(t) = x(t) - d_1(t). \quad (6)$$

This is called the sifting process. We have to judge whether $h_1(t)$ is an IMF. Ideally, $h_1(t)$ is an IMF, but in reality the envelope mean may not differ from the true local mean of the signal for nonstationary data, resulting in some asymmetric waveforms. Therefore, the sifting process has to be repeated k times until $h_{1k}(t)$ is an IMF. For the second sifting process, $h_1(t)$ is treated as the original data, then

$$h_1(t) - d_{11}(t) = h_{11}(t). \quad (7)$$

The sifting process is repeated k times until we find $h_{1k}(t)$, which is an IMF

$$h_{1(k-1)}(t) - d_{1k}(t) = h_{1k}(t). \quad (8)$$

Then we take

$$c_1(t) = h_{1k}(t) \quad (9)$$

as the first IMF component (i.e., component C1) from the data. Overall, C1 would contain the finest and the shortest period component of the signal, because a series of sifting processes for obtaining an IMF is essentially a process of high-pass filtering [9]. Subsequently, we can subtract $c_1(t)$ from the signal

$$x(t) - c_1(t) = R_1(t). \quad (10)$$

Because residue $R_1(t)$ still contains information about components with longer periods, we treat it as the new original data and apply the same sifting process as described above. This procedure can be repeated for all subsequent $R_f(t)$ values, yielding

$$R_1(t) - c_2(t) = R_2(t), \dots, R_{n-1}(t) - c_n(t) = R_n(t). \quad (11)$$

Summing Eqs. (10) and (11) finally yields

$$x(t) = \sum_{i=1}^n c_i(t) + R_n(t), \quad (12)$$

which indicates that $x(t)$ is decomposed by EMD into n IMFs and a residue $R_n(t)$, which is the signal trend or a constant. The next section will reveal how to design the algorithm of adaptive threshold filter using the EMD method.

3. Methods

3.1. Algorithm design

The goal of an adaptive threshold filter is to suppress the small echoes from backscattering without any deformation of local waveform associated with the preserved significant echoes due to reflection. Based on the characteristics of the C1 component obtained by the EMD, we have an idea to satisfy the requirements of an adaptive threshold. That is, we can purposely add an appropriate level of the artificial white noise into the ultrasound RF data and then apply the EMD of noisy RF data. The noise level is in a range between 0 and maximum of RF signal amplitude. The rationale why we do this is explained as follows. White noise has a very large bandwidth (infinite bandwidth in an ideal condition). It can result in the fluctuations with higher frequencies compared to RF signal, producing additional local extrema along the contour of the original RF signals. When the RF data contain additional noise, the local extrema in the echoes with larger amplitudes will be determined by the echoes themselves, whereas most of them come from the noise-induced high-frequency fluctuations for the small echoes. Under this condition, it can be expected that the C1 component just show the larger reflection signals, whereas the part corresponding to the small backscattering signals is replaced by a noise-scale baseline.

According to the above idea, we design the algorithmic steps of the adaptive threshold filter, as shown in Fig. 1, and describe the details as follows: (1) adding the artificial white noise into ultrasonic signals, (2) apply EMD of the noisy data, (3) taking the C1 IMF component as the filtered output. Here we want to emphasize a point. For the conventional threshold technique, there is no optimal threshold value. The threshold value in ultrasound systems is set to be adjustable so that users can determine the image quality they want. Identically, there is no optimal noise level for the use of adaptive threshold filter. Users can control the image quality by

Fig. 1. Flow chart for the algorithm of the adaptive threshold filter.

adjusting the level of added noise. Increasing the noise level in the RF data results in that more signals are rejected (i.e., like using a larger threshold value). In the next section, we will carry out both simulations and clinical measurements on the carotid artery for comparisons to validate the algorithm.

3.2. Simulations

We use a typical 1D model of ultrasound signal [10] to produce RF data to verify the algorithm of the adaptive threshold filter, as given by

$$RF = H \otimes Z, \quad (13)$$

where H is the Gaussian incident pulse and Z is the 1D scatterer distribution. Under a sampling rate of 100 MHz, we used an incident wave with a center frequency of 7.5 MHz and a bandwidth of 60% to generate the RF signal, which is shown in Fig. 2. Note that the strongest echo, indicated by the arrow, was contributed by a single strong reflector with a reflection coefficient 10-fold higher than those of scatterers in the background to represent the reflection echo. Compared to the weak background signals used to simulate backscattering echoes, we treat the largest reflection echo as the signal of interest (SOI). Subsequently, we added artificial white noise to the clean RF data in Fig. 2 to produce noisy RF signals with different SNRs. Specifying the power of the clean RF data as 0 dB, the SNR of the noisy RF signal was adjusted from 40 to 0 dB using the 'awgn' function in MATLAB software.

One point should be noted before applying EMD to the RF signals with different SNRs. Considering the randomness of the white noise, adding noise to the same signal at different times may produce noisy RF data with the same global waveform but different local characteristics. Therefore, to obtain reliable IMFs, white noise should be added and then EMD applied repeatedly several times. In our calculations, the IMF was obtained by applying EMD an

average of 30 times [11]. Note that the Ref. [11] reveals a new method called the ensemble empirical mode decomposition (EEMD), a noise-assisted EMD for time frequency analysis. The conclusion of our paper is very different from that of the reference, where the authors claimed the noise level is not important and they did not find the advantages and potentials of just adding weak noise into the signal as the application of adaptive threshold filtering.

3.3. Experiments

To explore the performance of the proposed adaptive threshold filter in practice, we carried out image measurements on the carotid artery to acquire the ultrasonic RF signals. The reason why we acquire carotid B-scan data is that the interface of the carotid artery in the B-mode image would be typically blurred by the small signals contributed from ultrasonic backscattering in blood and beam sidelobes that encompass the vessel walls and tissue regions. For this reason, the carotid image is suitable to be used to verify the proposed method. In the experiments, we scanned the carotid arteries of five volunteers using a commercial ultrasound scanner (Model 2000, Terason, Burlington, MA, USA). The applied transducer is a 7.5 MHz wideband linear array with 128 elements (Model 10L5, Terason, Burlington, MA, USA). The pulse length and the bandwidth were 0.5 μ s and 60%, respectively. The lateral beam-width is about 0.5 mm, and the focal length is adjustable from 3 to 16.5 cm. The sampling rate of the scanner to digitalize the raw RF data is 30 MHz. The signal interpolation was further performed to increase the sampling rate to 100 MHz to be the same as that of simulation. The carotid B-mode image was then formed using the log-compressed envelope image, which was obtained from the demodulation of each RF signal by taking its absolute values of Hilbert transform. The dynamic range of image display is 40 dB.

4. Results and discussion

Fig. 3 shows the IMFs obtained from EMD of the noisy RF signals with SNRs ranging from 40 to 0 dB. Note that the figure does not show all the IMFs of the RF signal for some cases. For an SNR of 40 dB, we found that the waveform of component C1 was nearly identical to that of the noisy ultrasonic signal, as shown in Fig. 3a. This is because the power of the added noise was much lower than that of the ultrasound signal when the SNR is 40 dB, and hence did not impact the local characteristics of the ultrasound signal. This means that the local extrema acquired from the noisy RF signal are entirely due to the ultrasound RF signal itself, and hence component C1 behaves like the original RF data but with a more symmetric waveform. On the other hand, we further found that different oscillatory modes of the RF signal were evident in IMF components C2 to C5. The oscillatory frequency decreases with increasing IMF index. Some of the final components (e.g., C6–C9) are empirically treated as the signal trends.

For an SNR of 20 dB (Fig. 3b), the largest reflection echo returned from the strong reflector (i.e., SOI) and some background signals from weak scatterers were extracted from the noisy RF data to form component C1. Moreover, the most background echoes with weaker amplitudes are assigned to component C2. The other

Fig. 2. 7.5 MHz, 60% fractional bandwidth simulated ultrasound signal (RF data).

Fig. 3. IMFs obtained from EMD of the noisy RF data for different SNRs: (a) 40 dB, (b) 20 dB, (c) 10 dB, and (d) 0 dB.

IMF components simply relate to oscillatory modes with lower frequencies, including signal trends in the ultrasonic backscattering. Comparison of Fig. 3a and b indicates that the noise level affects the results of EMD, which is further confirmed by the IMF results for the noisy signal with an SNR of 10 dB shown in Fig. 3c. Therefore, adding more white noise to the ultrasonic signal results in only the extracted SOI forming component C1, with the background signals and different oscillatory modes of the backscattered signal appearing in the subsequent IMF components. It should be noted that the preserved SOI does not have any deformation or change in the echo waveform. Referring to Fig. 3d for an SNR of 0 dB, when much more noise has been added, most local extrema acquired from the noisy RF signal would come from the noise-induced fluctuations, and thus component C1 simply describes the noise characteristics to mean that most echoes are rejected, with the SOI instead appearing in component C2.

The typical carotid ultrasound B-mode image is shown in Fig. 4a. We can note that the small echoes between upper and lower vessel walls pollute the image grayscale associated with the interface, making it difficult to clearly show the local details of some vessel walls. Here we try to use the proposed adaptive threshold filter to reject the small echoes in blood vessel to make the vessel interface in the B-scan clearer. At first, for each scan-line, we added white noise of different level by adjusting the signal SNR from 25 to 15 dB and then applied the EMD of noisy signal to form the B-mode images with the same dynamic range, as shown in Fig.

4b–d. Evidently, with decreasing the signal SNR (i.e., adding more noise), the small signals are gradually depressed so that the upper and lower vessel walls are differentiable. More importantly, the adaptive threshold filtering process does not cause any deformation of the waveform features for the preserved significant echoes due to reflection, as indicated by comparisons in Fig. 5. Obviously, the adaptive threshold filter performs better than the conventional threshold technique to reject the weak backscattering echoes without waveform distortions for reflection echoes. On the other hand, we further calculated the contrast-to-noise ratio (CNR) to explore the image contrast enhancement before and after applying adaptive threshold filtering. Here we only consider the image contrast between the vessel wall and blood flow area. Therefore, we purposely define the CNR by

$$\text{CNR} = 10 \log_{10} \left(\frac{\bar{P}_2}{\bar{P}_1} \right), \quad (14)$$

where $\bar{P}_1$ and $\bar{P}_2$ are the average powers of envelopes in the regions of interest (ROI) 1 and 2 in Fig. 4, respectively. Fig. 6 shows the CNR as a function of signal SNR we adjusted for adaptive threshold filter. It is obvious that the CNR increases from 17 to 32 dB with decreasing the signal SNR. It means that the adaptive threshold filter enhances the image contrast.

The experimental results have demonstrated that the adaptive threshold filter not only enhances the image contrast but also

Fig. 4. Typical 7.5 MHz B-mode images acquired from carotid artery using 1D, 128 elements linear array before (a) and after applying the adaptive threshold processing with different SNRs. (b) 25, (c) 20, and (d) 15 dB.

Fig. 5. Typical ultrasound RF signals acquired from carotid B-mode images before (a) and after applying the adaptive threshold processing with different SNRs. (b) 25, (c) 20, and (d) 15 dB. Note that the waveform features change after applying the conventional threshold filter. (e) Threshold value = 5.

allows the preservation of signal waveform. However, there may be some limitations when the adaptive threshold filter is used in practice, as discussed as follows. First, different ultrasound systems

would produce different dynamic ranges and different degrees of noise interference for the received ultrasonic RF signals from the same measured target. It means that there is no optimal level for

Fig. 6. The image contrast-to-noise ratio (CNR) as a function of signal SNR for adaptive threshold filter. The CNR was defined in Eq. (14) in Section 4.

the artificial noise added into the RF data to do adaptive threshold filtering. The noise level needed for filtering should be redetermined or corrected when using different measurement systems. Second, the adaptive threshold filter may not work when the original noise interference on the measured data is strong. This condition reduces the signal quality of the received RF data, making the filter output based on C1 mode of EMD become just a noise-based signal, like the example in Fig. 3d. Third, it has been shown that EMD is influenced by the sampling rate [12]. The bandwidth of the artificial white noise used for adaptive threshold filtering is also dependent on the sampling rate, because a half of the sampling rate determines the maximum bandwidth of the artificial noise according to Nyquist theorem. In other words, the sampling rate certainly affects the performance of the adaptive threshold filter. In the present study, a sampling rate larger than ten times the central frequency of ultrasound signal allows a production of approximately wideband noise, making adaptive threshold filtering successful.

5. Concluding remarks

This study has developed a novel adaptive threshold filter based on the empirical mode decomposition (EMD) for small signal rejection in ultrasonic images. The algorithm of the proposed method consists of two steps: adding artificial white noise to the ultrasonic

RF signal and then applying EMD to the noisy RF data to obtain the C1 component, the first component of EMD containing the finest and the shortest period component of the signal, as the filter output. Compared to the conventional threshold based on one value, the output of using the adaptive threshold filter to suppress the signals is determined by adjusting the level of noise added in the RF data (increasing the noise level produces a stronger threshold effect, rejecting more signals). To validate the algorithm and its feasibility in practice, we carried out the computer simulations and image measurements on the carotid artery by a commercial ultrasound scanner. The results demonstrated that the adaptive threshold filter is able to reject the small echoes produced from ultrasonic backscattering without changing the local waveform features of the significant echoes due to reflection. This not only enhances the image contrast but also allows the preservation of signal properties for signal quantitative analysis and tissue characterization.

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