Estimation and suppression of side lobes in medical ultrasound imaging systems

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Abstract This paper estimates the side lobe levels from the received echo data, and proposes and compares three types of filters that can be used to suppress them in an ultrasound image. Ultrasound echo signals from the off-axis scatterers can be modeled as a sinusoidal wave whose spatial frequency in the lateral direction of a transducer array varies as a function of the incident angle. The received channel data waveform due to side lobes have a spatial frequency of an integer plus a half. Doubling the length of the channel data by appending zeros and taking the discrete Fourier transform of the elongated data makes the spatial frequency of the channel data due to side lobes become an integer. Thus, it is possible to estimate the complex amplitude of the side lobes. Adding together all the channel data of the estimated side lobes, we can obtain the side lobe levels present in ultrasound field characteristics. We define the summed value as a quality factor that is used as a parameter of side lobe suppression filters. Computer simulations as well as experiments on wires in a water tank and a cyst phantom show that the proposed filters are very effective in reducing side lobe levels and that the amount of computation is smaller than that of the minimum variance beamforming method while showing comparable performance. A method of estimating and suppressing side lobes in an ultrasound image is presented, and the performance of the proposed filters is found to be

viable against the conventional B-mode imaging and minimum variance beamforming methods.

Keywords Estimation · Filter · Fourier transform · Minimum variance beamforming · Side lobe · Suppression

1 Introduction

Although a medical ultrasound imaging system is disadvantageous in that the imaging resolution is lower than X-ray and MRI modalities, there has been a continued progress in imaging performance due to advances in digital hardware technology. All digital implementation of the receive dynamic focusing made a breakthrough in enhancing ultrasound image quality [1]. The ultrasound image quality is determined by the ultrasound transmit and receive frequencies, transducer characteristics, transmit and receive focusing method, physical characteristics of ultrasound wave, etc. The diffraction of ultrasound wave and the nonuniform speed of sound in the human body are mainly responsible for degrading the focusing performance. The ultrasound image quality is influenced by the main lobe width as well as the side and grating lobe levels [2, 3]. Either the ultrasound transmit frequency or the transducer aperture size should be increased to improve the resolution. As the ultrasound transmit frequency increases, however, the attainable imaging depth decreases due to an increase in ultrasound attenuation. An array transducer is used for transmit and receive focusing of ultrasound signals. The array transducer consists of a number of small elements, and the interelement spacing should be less than one-half of a wavelength to prevent grating lobes. If we increase the transducer aperture, so does the number of

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array elements as well as the hardware complexity of a multichannel system for transmit and receive focusing.

Focusing is done to align in time and phase ultrasound signals at an imaging point. In transmit focusing, the transmit time at each element is varied so that ultrasound signals align in time and phase at a focal point. Exact transmit focusing can be done only at a single depth. However, the receive focusing can be done at all imaging points, since echo signals arriving at the individual array elements can be added together after compensating for different time delays. Therefore, when obtaining ultrasound images using transmit and receive focusing, the best resolution is possible only at the transmit focal point. To transmit focus at all imaging depths, the synthetic focusing method is used [4].

Once transmitted, ultrasound signals can no longer be controlled for focusing. Hence, using multiple stored frames, each of which is obtained at different time intervals, all-point transmit focusing is possible by applying different time delays required for transmit focusing and adding the processed frames together. Performing transmit and receive focusing at all imaging depths produces the highest-resolution image under the condition of diffraction-limited ultrasound wave propagation characteristics.

Application of digital signal processing to all received channel data can lead to improved image resolution. The channel data refer to the individual RF echoes received at the transducer array elements to which receive focusing delays are applied before delay and sum beamforming. Apodization is a technique commonly used to reduce side lobe levels, where weighting factors such as a Hamming window is applied to the received channel data [5]. The apodization processing uses the same window function at all imaging points, and has a disadvantage that the resulting main lobe width is increased. A method that applies a different window function at different imaging points is the MVB method [6–11]. The MVB method estimates an optimum window function at each imaging point using an optimization criterion to minimize the field response to the off-axis scatterers while maintaining the same field response to the on-axis scatterers.

Although there is a high degree of correlation between the received channel data originating from the on-axis scatterers, the amplitude and phase of signals originating from the off-axis scatterers vary depending on the channel into which those signals are stored. Therefore, the coherence between the received channel data can be used as a metric of the quality of focusing that measures the effect of the clutter signal on the on-axis signal. Methods of using the correlation between the channel data are coherence factor-based imaging and short-lag spatial coherence beamforming [12–14]. The phase coherence imaging

utilizes the correlation of the phase between them [15, 16]. Since the degree of coherence between the received channel data indicates the quality of focusing, the coherence factor itself was imaged, or it was multiplied to an image to improve its quality.

A method for improving the image quality was reported in which the received channel data were Fourier transformed and processed in the frequency domain [17–21]. Ultrasound signals reflected from an imaging point arrive at individual transducer array elements at different time instants depending on the distance between the imaging point and the array elements. From the perspective of spatial frequency, the signals coming from the main lobe direction arrive at the channels has the same time delay, which forms a dc frequency component across the transducer aperture, while the signals originating from the off-axis scatterers has a spatial frequency that varies with the incident angle with respect to the array transducer. Accordingly, signals coming from the off-axis scatterers take the form of a sinusoid across the transducer aperture and can have various spatial frequencies not equal to zero. By analyzing the frequency spectrum of the channel data after applying the focusing time delay, we can estimate the amplitude of a signal originating from the off-axis scatterers. Li and Li [17] computed weighting factors for improving ultrasound image quality using Fourier coefficients from the channel data. Dahl and Trahey [18] improved the estimation of phase aberration by filtering the change of phase in the frequency domain. Jeong [19] estimated the magnitude of side lobe signals by taking the Fourier transform of the received channel data, and filtered out the off-axis echoes. Byram et al. [20, 21] suppressed clutter using model-based off-axis signal. To improve ultrasound image quality, they modeled the off-axis channel data as a chirp signal and then estimated the chirp signal.

In our previous papers [22, 23], we applied receive focusing time delays to the received channel data based on ultrasound field characteristics, modeled the data as a sinusoidal wave, and estimated its waveform. Side lobe signals in the received channel data have spatial frequencies of an integer plus a half. Therefore, when estimating their spectrum using the discrete Fourier transform (DFT), the data length is doubled by appending with zeros, and the frequency of all side lobes becomes an integer. To reduce the computation time, the DFT is computed using fast Fourier transform (FFT). We define a qualify factor as a measure of indicating side lobe levels for use in three types of filters that improve ultrasound image quality. We have verified our proposed method by computer simulations and experiments, and showed the efficacy. We will explain the method in detail in subsequent sections, followed by side lobe filtering.

2 Background

Utilizing the relationship between the incident angle of side lobe and the spatial frequency, we estimated the side lobe waveforms by taking the Fourier transform of the received channel data [22, 23]. Although the relationship is explained in detail [12, 22], we provide a supplementary explanation.

Figure 1 shows the incident ultrasound wave and the resulting waveform across the channel data [24]. When an ultrasound pressure wave of continuous wave type impinges on an array transducer at an incident angle with it, it will arrive at each array element with the phase varying depending on the element position, thereby forming a sinusoidal wave across the transducer aperture. When an ultrasound wave of wavelength λ_o is incident at an angle of θ , the sinusoidal waveform across the transducer aperture, i.e., the x-axis, has a wavelength λ , which is given as

$$\lambda = \frac{\lambda_o}{\sin \theta} \quad (1)$$

Defining the number of cycles per aperture that the sinusoidal waveform has across the receive aperture as CPA, we have the following expression:

$$\text{CPA} = \frac{D}{\lambda} = \frac{D}{\lambda_o} \sin \theta \quad (2)$$

The CPA means the spatial frequency of a signal of interest that repeats itself in the spatial domain, i.e., across the transducer aperture, or the received channel data. The spatial frequency of the sine wave in Fig. 1 is 1 CPA, because the number of cycles across the receive aperture is equal to one.

Since the far field beam pattern of ultrasound wave is given by the Fourier transform of the aperture function, the field characteristic of a rectangular aperture takes the form of a sinc function [2]. Therefore, the field characteristic in

Fig. 1 The waveform of a sine wave across the receive aperture for an ultrasound wave of wavelength λ_o with an incident angle of θ

the vicinity of the main lobe can be approximately expressed as

$$f(x, z) = \text{sinc}\left(\frac{Dx}{\lambda z}\right) \quad (3)$$

where x and z denote the spatial coordinate, and $\text{sinc}(\cdot)$ is the sinc function. Figure 2 shows the relationship between the ultrasound field characteristic as a function of the incident angle and the corresponding channel data waveform. The abscissa in the field characteristic of Fig. 2 represents the incident angle, and is related to the spatial frequency by (2) and (3). Since the channel data received at the incident angles where the CPA is an integer are summed to zero as can be seen in Fig. 2, those angles correspond to the null positions in the field characteristic. Since for the incidents angles whose CPA is equal to an integer plus a half, the channel data cannot be summed to zero due to the presence of an additional half cycle, the nonzero sum corresponds to side lobes at those incident angles. Consequently, the side lobe levels can be approximately estimated by computing the channel data waveform at those incident angles where the CPA is equal to an integer plus a half.

3 Side lobe estimation

When ultrasound echoes are incident on an array transducer from many different directions simultaneously, the received channel data can be modeled as a sum of sinusoidal waves with different spatial frequencies [19, 22]. Denoting the complex amplitude of the component that has an integer frequency and that of the component that has a frequency of an integer plus a half by E_m and O_m , respectively, the received channel data can be written as

Fig. 2 The relationship between the incident angle in the ultrasound field characteristic and the spatial frequency of the sine wave

$$x_k = \sum_{m=0}^P E_m \cdot e^{j\frac{2\pi mk}{N}} + \sum_{m=1}^P O_m \cdot e^{j\frac{2\pi(m+0.5)k}{N}}, k = 0, 1, \dots, N-1 \quad (4)$$

where x_k is the echo signal received at the k th element among N transducer array elements, E_0 is the dc component of the channel data, m is the frequency index of nulls or side lobes up to the highest frequency index P . Note that the time index is omitted for brevity. By taking the DFT of the N -point channel data, we can exactly determine the magnitude of N integer frequency components [25].

$$x_m \xrightarrow{DFT(N)} X_m, m = 0, 1, \dots, N-1 \quad (5)$$

From (4) and (5), we have

$$E_m = X_m, m = 0, 1, \dots, N-1 \quad (6)$$

When adding together all the channel data in the receive focusing process, the sum of different frequency components whose complex amplitude is E_m equals E_0 because all frequency components other than E_0 cancel out.

Now we explain how to estimate the frequency component whose spatial frequency is an integer plus a half. We presented a method of making the spatial frequency of an integer plus a half appear to have an integer frequency by attaching a half cycle consisting of zero samples to the sinusoidal channel data [22, 23]. This method works, but to estimate the complex amplitude of side lobes of different frequencies, the window length needs to be varied, and the amount of computation increases.

Hence, we proceed to present a simpler approach. To estimate the complex amplitude of a sine wave with a spatial frequency of an integer plus a half, it suffices to double the frequency resolution of the spectrum before taking the DFT. This can be done by appending N zeros to the N -point data so that the total number of points becomes $2N$. We make the number of points in (5) equal to $2N$, and take the DFT. Then we have

$$x_m \xrightarrow{DFT(2N)} X_m, m = 0, 1, \dots, 2N-1 \quad (7)$$

It follows from (4) and (7) that the even and odd terms can be written as:

$$\begin{aligned} E_m &= X_{2m}, m = 0, 1, \dots, N-1 \\ O_m &= X_{2m+1}, m = 1, 2, \dots, N-1 \end{aligned} \quad (8)$$

From O_m obtained from the DFT, we obtain the channel data waveform of the corresponding side lobes as follows:

$$s_{m,k} = O_m \cdot e^{j\frac{2\pi(m+0.5)k}{N}}, k = 0, \dots, N-1 \quad (9)$$

where $s_{m,k}$ is the side lobe waveform of the m th frequency, and k is the channel number. Taking the DFT of the $2N$ point data, the complex amplitude of all side lobe

frequency components can be computed in a batch. Since the data lengths were different, the discrete-time Fourier transform (DTFT) of each side lobe was performed to compute the magnitude of each side lobe [22, 23]. In (8), however, the magnitude of all the side lobes is computed only once using FFT, resulting in its fast computational advantage.

After estimating up to the P th frequency side lobe waveforms, we add together all the estimated side lobes. Then the positive and negative sample values cancel out, and the resulting value represents the complex amplitude of side lobes.

$$sidelobe_P = \sum_{m=1}^P \left(\sum_{k=0}^{N-1} O_m \cdot e^{j\frac{2\pi(m+0.5)k}{N}} \right) \quad (10)$$

The value of $sidelobe_P$ represents the amount of clutter that degrades ultrasound image quality. By removing the clutter, we can improve the image quality.

4 Side lobe filtering

In this paper, we use three types of filters to address ultrasound image quality degradation due to undesired side lobes. We will show that $sidelobe_P$ in (10) as a parameter to control the performance of the filters can be used to improve ultrasound image quality. Since $sidelobe_P$ in (10) corresponds to the level of side lobes that degrade image quality, it is termed a quality factor, as follows:

$$QF_P = sidelobe_P \quad (11)$$

We have previously demonstrated that the adverse effect of side lobes can be alleviated by estimating and subtracting them in the receive focusing process [22, 23]. We refer to this filter as Type I filter. In this filter, the filtered output can be produced by subtracting the quality factor from the input data at each pixel.

$$B_{filtered} = B_{pixel} - QF_P \quad (12)$$

where B_{pixel} and $B_{filtered}$ is the image pixel brightness before and after filtering. It is known, however, that in an ultrasound imaging system that uses wideband pulses, Type I filter specified by (12) decreases the side lobe levels by more than 10 dB, but increases the main lobe width [22, 23]. To increase the effect of filtering, we design a nonlinear Type II filter, which can change image brightness depending on the clutter level [19]. The Type II filter can be designed as follows:

$$B_{filtered} = \left(\frac{B_{pixel}}{B_{pixel} + \gamma QF_P} \right) \cdot B_{pixel} = \frac{B_{pixel}}{1 + \gamma \frac{QF_P}{B_{pixel}}} \quad (13)$$

The effect of filtering can be controlled by adjusting scale factor γ and quality factor QF_P .

Type II filter is the same in form as the filter in [19], but to compute QF_P , the latter used the magnitude of the DFT coefficients corresponding to the clutter frequency components originating from the null or side lobe directions. In this case, echoes coming from the null directions does not affect ultrasound image because they add to zero, and the channel data magnitude due to echoes from side lobe directions cannot be accurately estimated. Combining (12) and (13) can reduce the clutter further. We introduce Type III filter by changing the filter input as follows:

$$B_{\text{filtered}} = \frac{B_{\text{pixel}} - QF_P}{1 + \gamma \frac{QF_P}{B_{\text{pixel}} - QF_P}} \quad (14)$$

The expression $QF_P / (B_{\text{pixel}} - QF_P)$ in the denominator of (14) is the ratio of the echoes from the off-axis scatterers to those from the on-axis scatterers.

5 Computer simulation

In this section, we carry out computer simulations to verify the proposed side lobe suppression filters. Using the received channel data to which the focusing time delays are applied, we estimated the channel data waveforms of side lobes and obtained B-mode images using the proposed filters. Computer simulations were performed first on point targets in water and then on cyst targets in a speckle background. The wideband pulse used in simulation is Gaussian shaped and has a duration of five cycles corresponding to the transducer center frequency. As shown in [22], when the channel data waveforms due to up to the 20th side lobes are estimated, the side lobe levels below -60 dB are removed. Accordingly, in this paper, we estimated up to the 20th side lobes. So the value of P is 20. All B-mode images are log compressed over a 60 dB dynamic range. The simulation conditions are shown in Table 1.

Table 1 Simulation conditions

Parameters	Values
Transducer	Linear array
Center frequency	7.5 MHz
Element pitch	0.2 mm
Number of receive channels	64 channels
Transmit focal depth	50 mm
Spatial frequency of side lobe	Up to 20
Log compression of image	60 Db

5.1 Point target imaging

We obtained the point spread functions (PSFs) by setting the transmit focal depth at 50 mm using a 64 element, 7.5 MHz center frequency linear array transducer. The lateral field response was simulated for a point target at a depth of 30 mm. The precision of the focusing time delays corresponded to a sampling rate of 240 MHz. Although the proposed side lobe estimation method is based on the continuous wave (CW) mode of operation, the performance of Type I filter for pulsed wave (PW) as well as CW excitations was compared.

Figure 3 shows the simulated lateral field responses of the PSFs before and after applying Type I filter for the case of CW and PW. The solid and dashed lines represent the PSFs before and after applying the filter, respectively. The graphs with and without ripples correspond to the case of CW and PW, respectively. The level of the first side lobe was decreased by 8 dB for CW and 10 dB for PW. Higher order side lobes were suppressed significantly. We can see that the proposed side lobe estimation method performs properly in the PW mode as well.

Figure 4 shows the simulated PW B-mode image of a point target at a depth of 30 mm. The image has a depth from 29 mm to 31 mm and a width from 2 mm to 10 mm. Each image was normalized to its maximum value and logarithmically compressed over a 60 dB dynamic range. In Fig. 4, (a) is the conventional PSF, (b) is QF_{20} , which is the magnitude of up to the 20th side lobes estimated, (c) is the result of applying Type I filter, (d) is the result of applying Type II filter with $\gamma = 10$, (e) is the result of applying type III filter with $\gamma = 10$. The image of QF_{20} in (b) is the result of extracting only the side lobes, and thus has the shape of letter X around the point target. The

Fig. 3 Simulated comparison of side lobe suppressing characteristics for the case of CW (with ripples) and PW (without ripples) before (solid) and after (dashed) using Type I filter

Fig. 4 The simulated B-mode images of a wire target at a depth of 30 cm using 60 dB log compression: **a** conventional imaging, **b** QF_{20} , **c** Type II filtering with $\gamma = 10$, and **e** Type III filtering with $\gamma = 10$

highest brightness in (b) is 13.41 dB less than that in (a). It can be seen in (c) that the side lobes are not perfectly suppressed with Type I filtering. For Type II and III filters, however, the effect of filtering out the side lobes can be observed.

Figure 5 compares the simulated lateral field responses of Fig. 4. For the case of applying Type I filter (dash), the first side lobe is suppressed, but a null appears at that point, increasing the main lobe width. For the case of applying Type II (dot) and III (dash-dot) filters, the first side lobe is

Fig. 5 Simulated comparison of the lateral field responses of a point target: conventional imaging (solid), Type I filtering (dash), Type II filtering with $\gamma = 10$ (dot), and Type III filtering with $\gamma = 10$ (dash-dot)

reduced by more than 20 dB, and the main lobe width is also reduced.

Figure 6 compares the full width at half maximum (FWHM) of the main lobe of the point target by applying Type II and III filters with varying values of γ . The FWHMs of the main lobes obtained using the conventional imaging (solid) and Type I filtering (dash) are 0.57 mm and 0.7 mm, respectively. The FWHMs of Type II and III filters are similar, and decrease and converge to 0.11 mm as the value of γ increases.

Figure 7 compares the change of side lobe levels with varying values of γ at the first side lobe position of the conventional imaging (solid). The side lobe levels of the conventional imaging (solid) and Type I filtering (dash) are -17 dB and -24 dB, respectively. For the case of Type II (dot) and III (dash-dot) filters, the side lobe levels decrease more significantly as the value of γ increases. Comparing Figs. 6 and 7, we can observe that the improvement in the field response is more pronounced with Type III filtering.

Figure 8 is the simulated B-mode images of point targets whose interelement spacing are 1, 2, and 3 mm, where (a), (b), (c), and (d) are the result of applying the conventional imaging, Type I filter, Type II filter, and Type III filter, respectively. The value of γ was set to 10. All the three filters are effective in reducing the side lobe levels, and the effect is most pronounced with Type III filter. Figure 9 compares the simulated lateral field responses of Fig. 8, and has the same trend as Fig. 5. However, the two wires interspaced by 1 mm display the interference of side lobes, and the magnitude of the main lobe decreases by 1.5 dB.

Figure 10 shows the simulated B-mode images of five adjacent wire targets separated by 2 mm whose reflectivity

Fig. 6 Simulated comparison of the FWHM of the main lobe with varying values of γ : conventional imaging (solid), Type I filtering (dash), Type II filtering (dot), and Type III filtering (dash-dot)

Fig. 7 Simulated comparison of the FWHM of the first side lobe levels with varying values of γ : conventional imaging (*solid*), Type I filtering (*dash*), Type II filtering (*dot*), and Type III filtering (*dash-dot*)

Fig. 8 The simulated B-mode images of three adjacent wire targets of equal reflectivity with interspacing of 1 mm, 2 mm, and 3 mm: **a** conventional imaging, **b** Type I filtering, **c** Type II filtering with $\gamma = 10$, and **d** Type III filtering with $\gamma = 10$

decreases to the right in steps of 10 dB, where (a), (b), (c), and (d) represent the B-mode images of the conventional imaging, Type I filtering, Type II filtering with $\gamma = 10$, and type III filtering with $\gamma = 10$, respectively. Figure 11 shows the lateral field responses of Fig. 10, where the solid, dashed, dotted, and dash-dotted lines represent the result of applying the conventional imaging, (b) Type I filter, (c) Type II filter with $\gamma = 10$, and (d) Type III filter with $\gamma = 10$, respectively. All the three filters reduce only the side lobe levels while also maintaining their respective reflectivity values. Figure 11 show similar results to Fig. 5, which is the case of a single point target.

Fig. 9 The simulated lateral field responses of three adjacent wire targets of equal reflectivity with interspacing of 1 mm, 2 mm, and 3 mm: conventional imaging (*solid*), Type I filtering (*dash*), Type II filtering with $\gamma = 10$ (*dot*), and Type III filtering with $\gamma = 10$ (*dash-dot*)

Fig. 10 The simulated B-mode images of five adjacent wire targets separated by 2 mm whose reflectivity decreases to the right in steps of 10 dB, where **a–d** are the results of applying the conventional imaging, Type I filtering, Type II filtering with $\gamma = 10$, and Type III filtering with $\gamma = 10$, respectively

5.2 Cyst imaging

A simulated numerical cyst phantom was generated by placing 100,000 point scatterers randomly within a volume of 30 mm × 25 mm × 5 mm. The scattering amplitudes were made to have a Gaussian distribution. An anechoic cyst containing no scatterers and a hyperechoic cyst whose reflectivity is 20 dB higher than that of the background, both of diameter 4 mm, were placed in the simulated numerical phantom. The center of both cysts was placed at a depth of 30 cm. The three point targets were placed at

Fig. 11 The simulated lateral field responses of five adjacent wire targets separated by 2 mm whose reflectivity decreases to the right in steps of 10 dB: conventional imaging (*solid*), Type I filtering (*dash*), Type II filtering with $\gamma = 10$, and Type III filtering with $\gamma = 10$ (*dash-dot*)

depths of 27 mm and 33 mm with the axial and lateral spacing of 6 mm. The image size covers an axial depth from 25 mm to 35 mm and a lateral width from 10 mm to 20 mm. We used the Field II ultrasound simulation program to reduce the computation time [26].

Figure 12 shows the B-mode images of the cysts obtained by applying various filters, where (a) is the conventional imaging; (b) is Type I filtering; (c), (e), and (g) in the left column are Type II filtering with $\gamma = 2$, $\gamma = 10$, and $\gamma = 100$, respectively; and (d), (f), and (h) in the right column are Type III filtering with $\gamma = 2$, $\gamma = 10$, and $\gamma = 100$, respectively. Because of the limited lateral resolution characteristic of the receive focusing system, the outer boundary of the anechoic cyst in the B-mode image of the conventional imaging is shrunk in the lateral direction so that it appears oval shaped. However, the outer boundary of the hyperechoic cyst appears to be stretched in the lateral direction. In the B-mode image of the conventional imaging, patterns due to side lobes can be observed inside the anechoic cyst. In the filtered images, however, those cannot be seen, and the outer boundary of the hyperechoic cyst is clearly delineated. In the case of Type II filtering, the side lobes around the point targets are not completely removed. Although the text pattern of speckle essentially does not change, and the brightness of the bright region remains almost the same with increasing value of γ , the dark region becomes darker, making most parts of the speckle region become darker.

Using the definition of the contrast ratio (CR), contrast-to-noise ratio (CNR), and signal-to-noise ratio (SNR) given in [14], we evaluated them to compare the statistics of speckle.

$$CR = 20 \log_{10} \left(\frac{S_c}{S_b} \right) \text{ (dB)} \quad (15)$$

$$CNR = \frac{|S_c - S_b|}{\sqrt{\sigma_c^2 + \sigma_b^2}} \quad (16)$$

$$SNR = \frac{S_b}{\sigma_b} \quad (17)$$

where S_c and S_b are the mean brightness values of the cyst and background in the image, respectively, and σ_c and σ_b are the standard deviations of the brightness of the cyst and background in the image, respectively. Table 2 presents the results. Each entry in the table corresponds to the panels of Fig. 12. The window regions corresponding to the cyst and background are indicated in Fig. 12a. In the anechoic region, with Type II and III filtering, the side lobe levels decreased with increasing value of γ . The C value of $-\infty$ was obtained because the side lobe inside the cyst region had been removed and thus the brightness value became zero. In the case of filtering, however, both CNR and SNR decreased as a result of the average brightness becoming darker in the speckle region. It can be seen that the image quality improved because of an increase in the contrast of the hyperechoic cyst.

6 Experiments

To confirm the performance of the proposed filters, 64 channel RF data before applying the receive focusing delay for all the scan lines were acquired on a wire and a cyst phantom using an ultrasound research platform (E-CUBE 12R, Alpinion Medical Systems, Seoul, Korea) [27]. The experimental conditions are the same as those of the simulations. All data were transferred to a PC and processed there using MATLAB. Using the experimental RF data, we compared the proposed filters and the MVB method of Kim et al. [11]. To this end we used (4) through (9) in their paper. The total number of channels was $M = 64$, the subaperture size for spatial smoothing was $L = 48$, and the diagonal loading factor for improving the robustness was $\Delta = 0.1$. We also used the combination of $L = 64$ and $\Delta = 0.01$. All images were logarithmically compressed over a 60 dB dynamic range.

6.1 Wire phantom

Two wire targets were placed at depths of 30 mm and 40 mm in a water target. Two additional wire targets were placed on the left and right side of the wire target at the depth of 40 mm. Figure 13 shows the B-mode images of the wire pattern, where (a) is the conventional imaging, (b) is Type I filtering, (c) and (e) are Type II filtering with

Fig. 12 Simulated comparison of processed cyst images: **a** conventional imaging; **b** Type I filtering; **c**, **e**, and **g** are Type II filtering with $\gamma = 2$, $\gamma = 10$, and $\gamma = 100$, respectively; and **d**, **f**, and **h** are Type III filtering with $\gamma = 2$, $\gamma = 10$, and $\gamma = 100$, respectively

Table 2 Simulated comparison of contrast, CNR, and SNR in anechoic and hyperechoic cysts

Anechoic cyst				Hyperechoic cyst				Background	
CR (dB)		CNR		CR (dB)		CNR		SNR	
(a) -16.33	(b) -51.10	2.54	3.00	6.43	6.32	2.30	2.27	3.34	3.01
(c) -30.52	(d) $-\infty$	2.51	2.24	6.84	6.94	1.93	1.93	2.62	2.24
(e) -72.48	(f) $-\infty$	1.58	1.57	8.68	8.34	1.59	1.64	1.58	1.57
(g) $-\infty$	(h) $-\infty$	1.06	1.13	11.2	10.05	1.44	1.48	1.06	1.13

$\gamma = 10$ and $\gamma = 100$, respectively, (d) and (f) are Type III filtering with $\gamma = 10$ and $\gamma = 100$, respectively, and (g) and (h) are the MVB with $L = 48$, $\Delta = 0.1$ and $L = 64$, $\Delta = 0.01$, respectively. The MVB method reduces the side lobe levels better with increasing subaperture size and decreasing diagonal loading factor. The experimental results are similar to the case of simulated point targets in the simulation. We can clearly see the X-shaped pattern in the conventional image, but not in the filtered images.

Figure 14 plots the magnitude of the signal passing through the middle wire at a depth of 40 mm, where the solid line is the conventional imaging, the dashed line is Type I filtering, the starred dashed and dotted lines are Type II filtering with $\gamma = 10$ and $\gamma = 100$, respectively,

and the crossed dashed and dotted lines are Type III filtering with $\gamma = 10$ and $\gamma = 100$, respectively. For the case of both Type II and III filtering, it can be seen that the side lobe levels as well as the main lobe widths are decreased.

In addition, Fig. 15 compares the magnitude of the signal passing through the middle wire at a depth of 40 mm, where the solid line is the conventional imaging, the dashed line is Type III filtering with $\gamma = 100$, the dotted and dash-dot lines are the MVB with $L = 48$, $\Delta = 0.1$ and $L = 64$, $\Delta = 0.01$, respectively. The main lobe width of the MVB method is smaller than that of Type III filter. The MVB method with $L = 64$ and $\Delta = 0.01$ and Type III filter showed similar side lobe suppression performance.

Fig. 13 The experimental B-mode images of wires in a water tank: **a** conventional imaging, **b** Type I filtering, **c** Type II filtering with $\gamma = 10$, **d** Type III filtering with $\gamma = 10$, **e** Type II filtering with $\gamma = 100$, **f** Type III filtering with $\gamma = 100$, **g** MVB with $L = 48$ and $\Delta = 0.1$, and **h** MVB with $L = 64$ and $\Delta = 0.01$

Fig. 14 Experimental comparison of the magnitude of the signal passing through the middle target at a depth of 40 mm: conventional imaging (*solid*), Type I filtering (*dash*), Type II filtering with $\gamma = 10$ (*dash-circle*), Type II filtering with $\gamma = 100$ (*dot-circle*), Type III filtering with $\gamma = 10$ (*dash-cross*), and Type III filtering with $\gamma = 100$ (*dot-cross*)

Fig. 15 Experimental comparison of the magnitude of the signal passing through the center of the middle target at a depth of 40 mm: conventional imaging (*solid*), Type III filtering with $\gamma = 100$ (*dash*), MVB with $L = 48$ and $\Delta = 0.1$ (*dot*), and MVB with $L = 64$ and $\Delta = 0.01$ (*dash-dot*)

6.2 Cyst phantom

To obtain RF data from a cyst with a speckle pattern, we used a precision small parts gray scale phantom (Gammex 404GS LE, Gammex, Middleton, WI, USA) [28].

Figure 16 shows the B-mode images of the hypoechoic and hyperechoic cysts, both of diameter 7 mm, at a depth of 30 mm using (a) conventional imaging, (b) Type I filtering, (c) Type II filtering with $\gamma = 10$, (d) Type III filtering with $\gamma = 10$, (e) Type II filtering with $\gamma = 100$, (f) Type III filtering with $\gamma = 100$, (g) MVB with $L = 48$ and $\Delta = 0.1$, and (h) MVB with $L = 64$ and $\Delta = 0.01$.

All the filtering methods except Type I filter are found to improve the resolution when imaging the wire targets. Type II and III filters exhibit coarse speckle patterns with increasing value of γ . Although the MVB method with $L = 64$ and $\Delta = 0.01$ in Fig. 16h appears to have the highest resolution for the wire targets, the speckle patterns before and after applying MVB are found to be very different. The filtering operations decrease both CNR and SNR due to a decrease in brightness in the speckle region, but increase CR. Other research results also report that the MVB method changes speckle statistics, and decreases image brightness and SNR. To address this problem, time averaging in range was adopted [7–9].

Table 3 summarizes the CR, CNR, and SNR parameters evaluated using the brightness values for the window regions in Fig. 16a.

Fig. 16 The experimental B-mode images of a 7 mm diameter cyst at a depth of 30 mm: **a** conventional imaging, **b** Type I filter, **c** Type II filtering with $\gamma = 10$, **d** Type III filtering with $\gamma = 10$, **e** Type II filter with $\gamma = 100$, **f** Type III filtering with $\gamma = 100$, **g** MVB with $L = 48$ and $\Delta = 0.1$, and **h** MVB with $L = 64$ and $\Delta = 0.01$

Table 3 Experimental comparison of contrast, CNR, and SNR within anechoic and hyperechoic cysts

Hypoechoic cyst				Hyperechoic cyst				Background	
CR (dB)		CNR		CR (dB)		CNR		SNR	
(a) -1.06	(b) -1.09	0.455	0.493	2.03	1.77	1.10	0.97	5.06	5.93
(c) -1.29	(d) -1.42	0.328	0.409	2.67	2.13	0.90	0.79	2.53	4.19
(e) -1.47	(f) -1.63	0.269	0.347	3.28	2.53	0.82	0.70	2.56	3.11
(g) -1.02	(h) -3.29	0.248	0.393	2.35	4.48	0.68	0.80	3.14	1.72

7 Discussion and conclusion

We estimated the side lobe waveforms from the received channel data to suppress echoes from the off-axis scatterers that degrade the resolution of a medical ultrasonic imaging system. Summing the estimated side lobe waveforms across the channels cancels out the positive and negative

sample values with the resulting summed value representing the magnitude of the side lobe. We can improve ultrasound image quality by merely subtracting the estimated side lobe component, but the degree of improvement is not significant. So we introduced two nonlinear filters whose parameter can be adjusted to control the amount of side lobe suppression. The nonlinear filters are found to be

very effective in reducing side lobe levels when imaging point targets. In cyst imaging, the contrast increased, and the speckle pattern in the background region became dark.

On the contrary, the effect of filtering when using experimental data was not as effective as in the simulation. This may be attributed to differences in sensitivity from one transducer channel to the next, errors in focusing delay computation in the imaging system, and phase aberrations arising from inhomogeneity in speed of sound [22]. However, we could obtain a large increase in contrast ratio when imaging cysts, which may aid us in diagnosing tumors in soft tissue. When imaging cysts, the MVB method produced the best results, but required a long computation time.

We compared the computation time for estimating side lobes using the `tic` and `toc` command of MATLAB on a laptop with an Intel Core i7 CPU operating at a clock frequency of 2.2 GHz and 8 GB of RAM. It took 329.3 μ s on average to estimate the spectrum of up to the 20th side lobe at a single imaging point using DTFT as in [22], but it took 16.2 μ s on average using 128-point FFT. Although the data length is doubled in our proposed method, using FFT is more efficient.

We compared the computation time for Fig. 16f, h. The time it took to read the RF channel data from the system memory, filter, quadrature demodulate, and produce an image was measured and averaged over 10 trials. Each of the 64 channels of RF data consists of 192 scan lines and 2816 samples per scan line. Our proposed filters are computationally very efficient because for each time index, both forward and inverse fast Fourier transforms need to be performed only once. The computation time for the MVB method and Type III filter is 920 s and 16.9 s, respectively. Thus, our proposed filtering method is faster than the MVB method by a factor of 54.4.

In this paper, we have proposed a method for estimating the side lobe levels and three types of filters, and compared the performance of side lobe suppression. Because the magnitude of the estimated side lobes, QF , is a metric of the fidelity of focusing the received signals, it can be used as a parameter in the proposed two types of nonlinear filters as well as in other nonlinear adaptive filters, to improve image quality.

The MVB method suppresses the side lobe levels in ultrasonic images and reduces the main lobe width, thus improving the resolution and aiding in lesion diagnosis. There are other researches that reduce the computation time of the MVB method for real-time operation using fast algorithms or graphics processing units [11, 29, 30].

Since our proposed method can improve ultrasonic image quality with a relatively smaller amount of computation than the MVB method, we expect that it may aid in

better diagnosis when incorporated into an ultrasound scanner.

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Conflict of interest Kwon SJ declares that he has no conflict of interest in relation to the work in this article. Jeong MK declares that he has no conflict of interest in relation to the work in this article.

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