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Autocorrelation-based generalized coherence factor for low-complexity adaptive beamforming

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ABSTRACT

Background: Generalized coherence factor (GCF) can be adaptively estimated from channel data to suppress sidelobe artifacts. Conventionally, Fast Fourier Transform (FFT) is utilized to calculate the full channel spectrum and suffers from high computation load. In this work, autocorrelation (AR)-based algorithm is utilized to provide the spectral parameters of channel data for GCF estimation with reduced complexity.

Methods: Autocorrelation relies on the phase difference among neighboring channel pairs to estimate the mean frequency and bandwidth of channel spectrum. Based on these two parameters, the spectral power within the defined range of main lobe direction can be analytically computed from a pseudo spectrum with the presumed shape as the GCF weighting value. A bandwidth factor Q can be further included in the formulation of pseudo channel spectrum to optimize the performance.

Results: While the GCF computation complexity of a N-channel system reduces from $O(N\log_2 N)$ with FFT to $O(N)$ with AR, the lateral side-lobe level is effectively suppressed in the GCF-AR method. In B-mode speckle imaging, the GCF-AR method can provide a higher image contrast together with a relatively low speckle variation. The resultant Contrast-to-Noise Ratio (CNR) improves from 6.7 with GCF-FFT method to 9.0 with GCF-AR method.

Conclusion: GCF-AR method reduces the computation complexity of adaptive imaging while providing superior image quality. GCF-AR method is more resistant to the speckle black-region artifacts near strong reflectors and thus improves the overall image contrast.

1. Introduction

Dynamic focus beamforming in ultrasound array system is routinely performed by applying time delay to the received echo in each channel according to the geometric path of propagation. To achieve focusing, the delayed echoes in channels are coherently summed for signal amplification. This is generally referred to as the delay-and-sum (DAS) approach. In DAS, transmit-receive aperture apodization determines the lateral side-lobe level (LSLL). Since the presence of lateral side lobes will reduce the image Contrast-to-Noise Ratio (CNR) and thus degrade the detectability of small lesions, a smooth apodization such as Hanning function can be applied to reduce the LSLL but at the cost of lateral main-lobe width [1]. In other words, there is a tradeoff between the image contrast and the image resolution in the design of aperture apodization. On the other hand, sound-velocity inhomogeneities in the human body produce errors in the estimation of time delay and further elevate the LSLL. In order to provide effective side-lobe suppression without degradation of image resolution, many methods have been proposed to adaptively correct the focusing errors in the DAS processing. For example, before summing the channel signal, delay compensation can be performed by cross-correlation between signals from adjacent channels [2–4]. Adaptive beamforming can be also performed to directly constrain the side-lobe energy by optimizing apodization coefficients for each receive channel [5–8] or by using parallel adaptive receive compensation algorithm [9–11].

Another method of adaptive imaging is to avoid the appearance of focusing errors in conventional DAS image. Specifically, focusing quality has to be estimated for each image pixel and then low-quality pixels are suppressed in the image by reducing their display magnitude. In other words, the DAS image is multiplied by an adaptive weighting matrix based on the pixel-by-pixel focusing

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quality [12–14]. For example, the coherence factor (CF) [15], which is defined as the ratio between the power of the coherent component and the total power in the channel data, has been proposed an index of focusing quality. When the echo is coming from the main lobe of the acoustic beam, the channel data exhibits high coherence and thus has a high CF. On the contrary, the CF decreases if the side-lobe component dominates the received channel data. By scaling the DAS image by the CF value, on-axis components are preserved while the off-axis components are suppressed in the final image. The CF-based method provides good contrast enhancement but may introduce black-region artifacts in the speckle pattern [16].

The black-region artifacts can be alleviated by generalizing the CF value to include the incoherence nature of speckle signal. Specifically, generalized coherence factor (GCF) is developed by using spatial spectrum of the channel data to estimate the signal power from not only the on-axis direction but also a range of pre-defined main-lobe directions. Generally, a Mo value can be specified to define the range of main-lobe component in the Fast Fourier Transform (FFT) channel spectrum [17]. The signal power in the channel spectrum ranging from −Mo to +Mo is combined to represent the main-lobe power. In other words, when Mo = 1 is adopted, the main-lobe power comes from the DC component and one neighboring low-frequency component in each side of the FFT power spectrum. Note that, with Mo = 0, the GCF weighting degenerates to CF weighting since only the DC component (i.e., the coherent power) is utilized to estimate the main-lobe signal power. Note that the estimation of GCF value demands for one FFT operation for every image pixel and each FFT operation requires $(N/2)\log_2 N$ multiplications for N-channel array system. For example, when a 96-channel system is utilized to construct the image of 100 scan lines in the lateral direction and 1000 samples in the axial direction, it takes about 32 million multiplications to calculate the GCF weighting matrix for each frame. Therefore, the computational complexity of GCF adaptive weighting can be a problem, especially for low-end system. It should be noted that, however, the presence of tissue motion does not pose difficulties in GCF estimation because the adaptive weighting is calculated for each scan line in the sequence of B-mode scanning and thus relies on the channel data from only single transmission.

In this study, it is proposed that the GCF weighting can be efficiently approximated by using the autocorrelation (AR) of the channel data to estimate the mean and the variance of the spatial spectrum. Assuming the spatial spectrum has a certain shape of spectral distribution, a normalized pseudo spectrum can be readily constructed based on the estimated spectral mean and variance and the GCF weighting can be obtained with reduced computational complexity. The paper is organized as following: Section 2 introduces the AR estimation of channel data and how the estimated spectral mean corresponds to the incident angle of the received echoes. Calculation of AR-based GCF weighting value using a pseudo spectrum is also explained in details. Section 3 describes the simulation and experimental setup used in this study. In the simulations, comparison of radiation pattern and LSLL between the FFT-based and AR-based GCF weighting methods are provided. In the experiments, B-mode images with quantitative analysis of image quality are also included. The paper concludes in Section 4 with discussions about potential limitation of the proposed method.

2. AR-based GCF weighting (GCF-AR)

In ultrasound imaging system, autocorrelation has been widely implemented to provide Doppler spectral parameters for real-time color flow estimation with low computational complexity. Instead of computing the complete Doppler spectrum, autocorrelation estimates the mean Doppler frequency in the temporal domain from the phase change between adjacent Doppler samples. For example, when the Doppler samples (S_i) are acquired with a sampling period (T) for $i = 1 \sim N$, the phase change in each of $(N-1)$ adjacent pair (S_i and S_{i+1}) is calculated by multiplying the current sample by the conjugate of the previous sample. Since the phase change corresponds to the displacement of imaged objects during one T, the mean Doppler frequency ($\bar{\omega}$) can be estimated as in the following [18]:

$$A_1 e^{j\theta_1} = \frac{1}{N-1}\sum_{i=1}^{N-1} S_i^* S_{i+1} \tag{1}$$

$$\bar{\omega} = \frac{\theta_1}{T} \tag{2}$$

where the magnitude and the phase of the first-lag autocorrelation are represented as A_1 and θ_1 respectively. When the mean Doppler frequency alone does not suffice to represent the Doppler spectrum, estimation of the spectral variance (σ_ω^2) can also be included to describe the Doppler bandwidth by the ratio of A_1 to A_0 (i.e., the magnitude of the zero-lag autocorrelation):

$$A_0 = \frac{1}{N}\sum_{i=1}^{N} S_i^* S_i \tag{3}$$

$$\sigma_\omega^2 = \frac{2}{T^2}\left[1 - \frac{A_1}{A_0}\right] \tag{4}$$

Similar to the aforementioned Doppler estimation in the temporal domain, reduction of computation complexity in GCF estimation can be also achieved by using autocorrelation in the spatial domain to generate essential spectral parameters of channel data. Note that the channel data is actually the spatial samples of echo wavefront with the sampling spacing of array pitch (d). Therefore, when S_i now represents the received echo in the i-th channel after delay compensation in the dynamic focus beamforming, Fig. 1 demonstrates that the mean of phase change between adjacent channels can be related to the incident angle (ϕ) of echo wavefront relative to the on-axis direction by the following equation:

$$\sin\phi = \frac{\theta_1}{d}\frac{\lambda}{2\pi} \tag{5}$$

In other words, by simply replacing the temporal sampling period T in (2) with the spatial sampling spacing d, the autocorrelation of channel data can be utilized to estimate the incident angle of the received echoes. When the incident angle is close to zero, the echo is coming from the on-axis main-lobe region. Otherwise, when the imaged object is situated in the off-axis side-lobe region, the corresponding incident angle will deviate from zero. For N-channel array system, the incident angle of echo wavefront in the AR-based estimation corresponds to the spatial frequency in the FFT-based estimation by $\sin\phi = \lambda n/Nd$ where $n = 0 \sim (N/2) - 1$ if N-point FFT is utilized to calculate the channel spectrum. Similarly, variation of incident angle can also be calculated to represent the angular diversity of scattering within the acoustic beam:

$$\sigma_{\sin\phi}^2 = \frac{2}{d^2}\left[1 - \frac{A_1}{A_0}\right]\left(\frac{\lambda}{2\pi}\right)^2 \tag{6}$$

Note that, when both zero-lag autocorrelation and first-lag autocorrelation are required for the AR estimation of spectral mean and variance, it takes $(2N-1)$ multiplications for one image pixel. Compared to the FFT estimation, the computational complexity has