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Low complex subspace minimum variance beamformer for medical ultrasound imaging

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ABSTRACT

Minimum variance (MV) beamformer enhances the resolution and contrast in the medical ultrasound imaging at the expense of higher computational complexity with respect to the non-adaptive delay-and-sum beamformer. The major complexity arises from the estimation of the $L \times L$ array covariance matrix using spatial averaging, which is required to more accurate estimation of the covariance matrix of correlated signals, and inversion of it, which is required for calculating the MV weight vector which are as high as $O(L^2)$ and $O(L^3)$, respectively. Reducing the number of array elements decreases the computational complexity but degrades the imaging resolution. In this paper, we propose a subspace MV beamformer which preserves the advantages of the MV beamformer with lower complexity. The subspace MV neglects some rows of the array covariance matrix instead of reducing the array size. If we keep η rows of the array covariance matrix which leads to a thin non-square matrix, the weight vector of the subspace beamformer can be achieved in the same way as the MV obtains its weight vector with lower complexity as high as $O(\eta^2 L)$. More calculations would be saved because an $\eta \times L$ covariance matrix must be estimated instead of a $L \times L$. We simulated a wire targets phantom and a cyst phantom to evaluate the performance of the proposed beamformer. The results indicate that we can keep about 16 from 43 rows of the array covariance matrix which reduces the order of complexity to 14% while the image resolution is still comparable to that of the standard MV beamformer. We also applied the proposed method to an experimental RF data and showed that the subspace MV beamformer performs like the standard MV with lower computational complexity.

1. Introduction

Array transducers in medical ultrasound imaging facilitate forming images with focused beams. Appropriate delays and weights are applied to the received signals at each array element to form an arbitrary beampattern which can focus on the desired direction. Delay-and-sum (DAS) beamformer is a conventional data-independent beamformer due to its easy and low cost implementation. This beamformer chooses a pre-defined weight vector despite of the incoming data to form an image. However, the classic problem dealing with the DAS is a trade-off between the mainlobe width and sidelobe levels. The narrower mainlobe, which causes better lateral resolution, increases the sidelobe levels, leading to worse contrast, and vice versa. Aperture shading is used to find the proper weight vector for desired resolution but the limitation is still remained; resolution and contrast cannot be improved simultaneously [1].

Adaptive beamformers have been investigated to overcome the problem of DAS beamformer. These beamformers use the incoming data to obtain the apodization vector at each imaging point instead of choosing a fixed weight vector. An adaptive beamformer recently applied in medical ultrasound imaging is the minimum variance (MV) beamformer. This beamformer maximizes the output signal to interferences plus noise ratio (SINR) while preserving the power in the desired direction. MV beamformer offers better resolution and contrast due to its capability to suppress the interferences. Various approaches to apply the MV beamformer and improve its performance in medical ultrasound imaging have been addressed in the literature [2–6].

The main problem of the MV beamformer is its high computational complexity. Specifically, the complexity of the DAS beamformer is linear with the number of array elements, $O(M)$, while the complexity of the MV beamformer is as high as $O(M^3)$ due to the inversion of the array covariance matrix. This higher order of complexity makes it difficult to implement the MV as a real-time beamformer when the number of array elements increases. So, reducing the computational complexity while

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retaining the benefits of the MV beamforming would be necessary for real-time implementation.

Recently, several approaches have been proposed to reduce the computational complexity of the MV beamformer. Nilsen and Hafizovic [7] applied the beamspace adaptive beamformer in ultrasound imaging which maps the received data to a set of orthogonal beams. Using the new projected data with lower dimension, the size of the array covariance matrix can be reduced to the number of selected beams instead of the number of subarray elements and as a consequence, complexity reduces significantly. Synnevag et al. [8] proposed a beamformer which selects a window from a list of predetermined windows that minimizes the output power. In other words, it chooses the apodization weights at each point separately and depending on the incoming data. This method reduces the complexity to that of the DAS beamformer multiplied by the number of predefined windows. The performance of this beamformer is much related to its windows and hence, for different scenarios, choosing appropriate windows would be necessary. A different low complex method has been suggested by Asl and Mahloojifar [9] in which they showed that assuming spatial stationarity is a good approximation in medical ultrasound applications, allowing us to apply the Toeplitz structure to the estimated covariance matrix. Dimension reduction using principal component analysis (PCA) has been proposed by Kim et al. [10]. They used a transformation matrix achieved by eigen-decomposition of a set of weight vectors obtained by a predetermined phantoms and approximated the MV weights by a linear combination of a few selected dominant principal components. The complexity of this beamformer is same as the beamspace beamformer. The performance of this fast MV beamformer depends on the training set which should be chosen as close as possible to the real imaging environment. Another approach has been suggested by Sakhaei [11]. He proposed decimating the received signals along spatial domain in which the decimated data with reduced dimension, leads to estimate the lower-dimension array covariance matrix that can be inverted with less computational complexity. Real-time implementation of the MV beamformer for cardiac imaging has been claimed by Asen et al. [12]. They used the parallel processing power in graphic processing unit (GPU) combined with the beamspace beamformer to real-time implementation of the MV beamformer. Since the MV obtains the weights at each point independently, this process can be done with a parallel strategy. While, GPU and its ability to parallelize the time consuming tasks make it feasible to use complex algorithms in real-time imaging, the demand to reduce computational complexity is still alive. Low complex imaging approaches with GPU's power facilitate making images with higher frame rates and lower pixel spacing.

In this paper, we propose a subspace MV beamformer for ultrasound imaging that maintains the advantages of the MV beamformer with lower computational complexity. The main idea of this beamformer is based on the subspace beamformer proposed by Choi [13]. In this beamformer, instead of removing elements in the array or mapping data to a new space, some rows of the array covariance matrix would be removed. With new non-square matrix, the optimization criteria of the MV beamformer can be followed to obtain weight vector adaptively. In other words, the subspace MV beamformer efficiently obtains the weight vector from a submatrix of the received signal covariance matrix without eigen-decomposition, leading to significant reduction of the computational complexity. If we keep η rows of the $L \times L$ array covariance matrix, the complexity of the proposed method to obtain the weight vector decreases to $O(\eta^2 L)$ in comparison to $O(L^3)$ for that of the standard MV. Further complexity reduction can be considered, because there is no need to estimate the full array covariance matrix and only we need to estimate an $\eta \times L$ matrix. We also propose that the procedure of determining the required number of rows can be done using generalized coherence factor (GCF) [14] by measuring the coherency of the incoming signals. Simulations demonstrated that for the wire and cyst phantoms, the number of rows can be selected as low as $\frac{16}{43}$ of the subarray length which means a reduction in computational complexity to 14% of the MV beamformer while the resolution and contrast are still comparable to that of the MV beamformer.

The rest of the paper is organized as follows. The second section explains the background about the MV beamformer and its implementation issues. At the third section, we explain the subspace MV beamformer and its requirements to be applied in the medical ultrasound imaging in detail. The results of simulations have been presented in Section 4. Some different simulated phantoms and an experimental data have been used to evaluate different aspects of the proposed beamformer. Discussion about the proposed beamformer and its ability to reduce the computational complexity is provided in Section 5. Finally, the conclusion has ended the paper.

2. Background

The proposed method is based on the optimization criteria of the MV beamformer, so it would be necessary to explain how the MV deals with received data and obtains the weight vector. The background has been provided to introduce the MV beamformer in the medical ultrasound imaging.

2.1. Minimum variance beamformer

In pulse-echo ultrasound imaging, a short-time pulse is sent to the medium and the backscattered echoes are recorded to form the image. Focusing is possible by applying appropriate delays to signals in the transmit and receive. Received data to an ultrasound array can be considered as:

$$\mathbf{x}(k) = \mathbf{A}\mathbf{s}(k) + \mathbf{n}(k), \tag{1}$$

where $\mathbf{x}$ is the received data, $\mathbf{x}(k) = [x^0(k), x^1(k), \ldots, x^{M-1}(k)]$, $\mathbf{A}$ is the steering matrix, $\mathbf{s}$ is the vector of sources, $\mathbf{n}$ is the added white noise, k is the time index and M is the number of array elements. The sources are in the imaging plane and we are trying to find the desired source among the others and the interferences with the beamforming techniques. Without any compromising, we can assume one desired source in the medium and the rest of the sources are considered as the interferences;

$$\begin{aligned} \mathbf{s}(k) &= [s_d(k)\; s_{i_0}(k)\; s_{i_1}(k) \ldots], \\ \mathbf{A} &= [\mathbf{a}\; \mathbf{A}_I], \end{aligned} \tag{2}$$

where s_d is the desired source, $s_{i_0}, s_{i_1}, \ldots$ are the interferences, $\mathbf{a}$ is the steering vector in the desired direction and $\mathbf{A}_I$ is the steering matrix of the interferences. It is assumed that signals have been delayed, so the final output of the beamformer is the weighted sum of the delayed received data which can be written in the vector form:

$$y(k) = \mathbf{w}^H(k)\mathbf{x}_d(k) = \sum_{i=0}^{M-1} w^*(k)x^i(k - \tau_i), \tag{3}$$

where y is the output of the beamformer, $\mathbf{w}$ is the complex weight vector, H stands for the Hermitian transpose, $\mathbf{x}_d$ is the time-delayed signal, $*$ is the conjugate operator and τ_i is the appropriate delay to focus at the desired point.

The MV beamformer obtains the weight vector $\mathbf{w}$ in a way that it maximizes the output SINR without any distortion in the desired direction. So, the maximizing problem can be written as: