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A low complexity beamformer for volumetric arrays using two stage Beam-Space and Sub-Array processing

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Abstract: Advantages of line arrays include simplified construction and ease of mechanical handling. However, an important shortcoming is their inability to resolve left-right ambiguity since line arrays can only measure conical angle. Since appropriate volumetric arrangements of hydrophones are able to uniquely measure azimuth and elevation angle and thus resolve left-right ambiguity, there is much interest today in the use of towed volumetric arrays as passive sonar receivers. This paper considers the development of adaptive beamforming algorithms using Beam-Space transformation for a prototype volumetric array.

Keywords: beamformer, krylov space, triplets

1 Introduction

Linear towed arrays are used in target detection and tracking in underwater applications. Volumetric arrays are desirable in passive sonar systems because of their ability to resolve left-right ambiguity. However, adaptive beamforming of volumetric arrays poses several unique challenges compared to linear arrays such as the large number of hydrophones, lack of sample support, the necessity to know accurately the x,y,z positions of all the elements, and the correlated structure of the ambient noise, even when it is isotropic. The prototype volumetric array under consideration (Fig.1) consists of M triplet sets of hydrophones arranged as identically oriented equilateral triangles with sides of length d and separated by distance L. All the array components (hydrophones and electronics) are embedded in a flexible oil-filled hose for towing and storage.

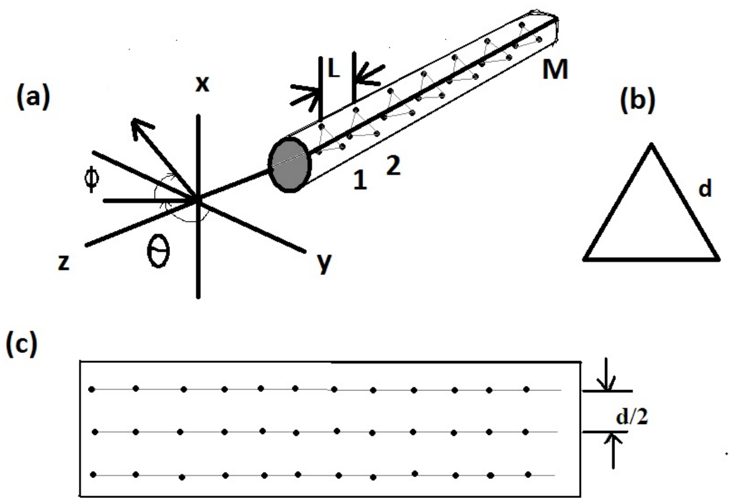

Figure 1: Protype Volumetric array: (a) Geometry (b) Triplet arrangement of hydrophones on equilateral triangle (c) Linear subarray view of array from top.

1.1 Data model and adaptive beamforming

Using the standard narrowband signal assumption [1], the data snapshot measured by the array at time t is modeled as

$$\bar{x}_t = \sum_{m=1}^{k} a_m(t)\bar{s}(\theta_m, \phi_m) + \bar{n}(t) \tag{1}$$

where $\bar{s}(\theta_m, \phi_m)$ and $a_m(t)$ are the signal modes or spatial replicas and complex amplitude of the m-th signal source respectively arriving from azimuth angle θ and elevation angle ϕ. $\bar{n}(t)$ is some ambient noise component. The objective is to detect the presence of the signals and estimate their directions of arrival from the measurements $\bar{x}_{t1}, \bar{x}_{t2}, \ldots, \bar{x}_{tN}$.

Since the directivity and left-right resolution of this array is poor, some form of adaptive beamforming [1, 2] is necessary. One popular adaptive beam former (ABF) used in underwater acoustic signal processing applications is the Minimum Variance Distortionless Response (MVDR) method.

$$z(\theta, \phi) = \frac{1}{\bar{s}^H_{\theta,\phi} \, R^{-1} \, \bar{s}_{\theta,\phi}} \tag{2}$$

where H is the Hermitian conjugate and

$$R = E\{x, x^H\} \tag{3}$$

is the sample covariance matrix.

1.2 Challenges in adaptively beamforming a volumetric array

Adaptively beamforming the prototype volumetric array in Fig.1 is much more challenging than a linear array of the same length. The foremost problem is the high dimensionality (3M vs. M) of the volumetric array since the performance of matrix inverse-based adaptive beamformers is related to the proportionality of data snapshots to the system dimensionality [2]. Dynamic characteristics of the signal sources and array may not provide sufficient time to obtain enough data snapshots for satisfactory performance or nonsingular sample covariance matrices.

Another complication is that the 3-D element arrangement and element closeness in this array (element spacing are considerably less than the signal wavelength λ, that is, $d < L \ll \lambda$) results in even spherically isotropic noise having highly correlated and structured noise measurements $\bar{n}$ and nearly singular covariance matrices at low frequencies.

The last concern of course is sensitivity to steering vector mismatch. Adaptive beamformers can be extremely sensitive to mismatch, especially if the covariance matrix is ill conditioned or nearly singular as it is here [1, 2]. Common sources of mismatch include uncompensated hydrophone gain and phase errors, uncertainty in the element positions, and signal wavefront perturbations due to medium effects. The volumetric array in Fig. 1 is also prone to torsional twisting from tow cable forces and thus is especially sensitive to mismatch in y and z because of the closeness of the elements relative to the signal wavelength.

2 Beamformers

2.1 Planar beamformer

In a planar beamformer, the volumetric array is treated as three single arrays to which first straightforward conventional beamforming is applied. The output of this process is a set of three array beam patterns that are still ambiguous. Conventional beamforming is applied to these beam patterns so as to remove the L/R ambiguity. The disadvantage of this method is that since the radius of the triplet array is small, the noise received on the three hydrophones in a triplet is highly correlated thereby reducing the L-R Rejection Ratio(LRRR).

For simulation purpose, we consider 3 linear arrays with 32 sensors each to form a volumetric array consisting of 96 elements. The signal frequency is assumed to be 2kHz. The array specifications are $L = 0.3375$m, $d = 0.1688$m. Fig.3 shows the L-R rejection ratio versus bearing angle plot for three different SNR values.

2.2 Optimum triplet beamformer

In this method noise decorrelation is achieved by forming adaptive beams on the ambiguous beam patterns[3]. Since the elements of the triplet are closely spaced, we can model the

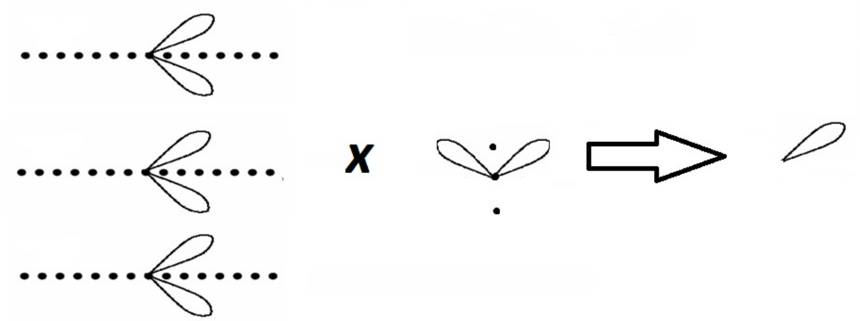

Figure 2: L/R ambiguity resolution using Planar Beamformer

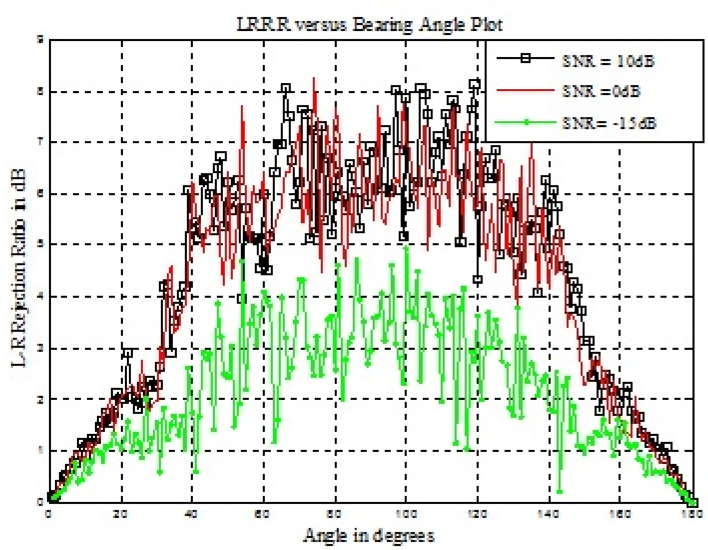

Figure 3: LRRR versus bearing angle plot for planar beamformer

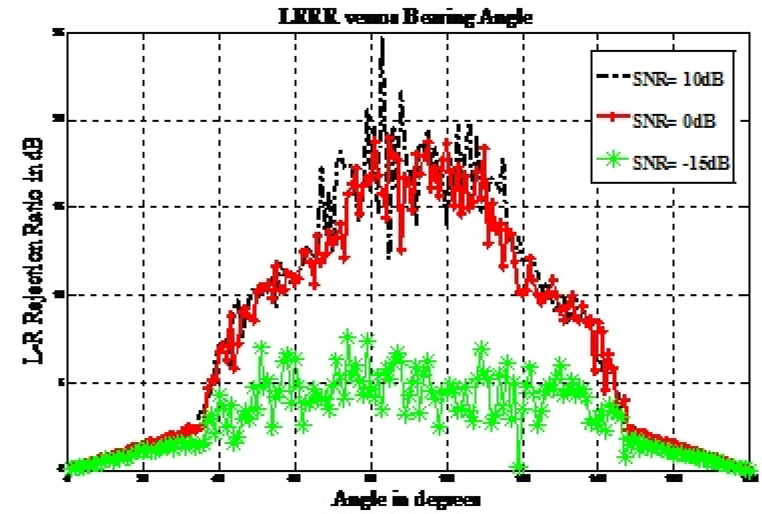

Figure 4: LRRR versus Bearing angle plot for Optimum Triplet Beamformer

noise correlation matrix, R_n as

$$R_n = \begin{bmatrix} 1 & \rho & \rho \\ \rho & 1 & \rho \\ \rho & \rho & 1 \end{bmatrix}. \tag{4}$$

Here the correlation coefficient ρ is modeled as

$$\rho = \frac{\sin c\left(kr\sqrt{3}\right)}{1+\sigma^2} \tag{5}$$

To illustrate the performance of optimum triplet beamformer, we assume the same array characteristics as that we used for planar beamformer. Fig.4 shows the L-R rejection ratio versus bearing angle plot for optimum triplet beamformer. It is evident from figure that L-R rejection ratio is improved in optimum triplet beamformer method.

2.3 Beam-Space and Sub-Array processing

The problem of inadequate sample support (that is, singular sample covariance matrices) can be addressed by dimensionality reduction, that is, reducing the array degrees of freedom to less than or equal to the number of available data snapshots.

A much simpler approach for dimensionality reduction is a two-stage procedure based on Beam-Space preprocessing followed by adaptive beamforming [2, 4]. The fundamental idea is to first reduce the dimensionality of the element space data by a lower dimension linear transformation, say steering conventional delay-sum beams at each of the signal and interfering sources and then adaptively processing or combining the beam outputs.

The idea is to reduce the dimensionality of the element space data by a lower dimension linear transformation [5, 6]. Here we estimate linear sub array subspace S adaptively by an expanding Krylov subspace using a subarray steering vector pointing to a desired spatial direction S_L as

$$||S|| = K_r(R, S_L)$$

Thus, the Beam-Space dimensionality reduction is done using the following equations

$$Q = T^H RT, \quad S_B = T^H S \tag{6}$$

where

$$T = \begin{bmatrix} S & 0 & 0 \\ 0 & S & 0 \\ 0 & 0 & S \end{bmatrix}$$

and Q is the reduced dimension cross spectral density matrix.

Finally, adaptive beamforming is done on this reduced dimension matrices and the power is computed as follows.

$$P = \frac{1}{s_B^H Q^{-1} s_B}. \tag{7}$$

Fig.5. shows the block diagram implementation of two stage Beam-Space and Sub-Array processing.

3 Results

We have simulated the two stage Beam Space and Subarray processing methods by considering a volumetric array of 96 sensors. Each linear array is assumed to be consisting of 32 elements separated by a distance of $d = 0.1688$m. The beam space transformation matrix is chosen to be of size 8×8. Fig.6 shows the Left-Right ambiguity resolved plot for target angle $100°$. Fig.7 shows the L-R rejection ratio versus bearing angle plot for two stage Beam-Space and Sub-Array processing methods.

4 Conclusions

The proposed two stage Beam-Space and Sub-Array processing methods have greatly reduced degrees of freedom, permitting operation with singular sample covariance matrices in situations of small sample support. Furthermore, it is inherently robust against steering vector mismatch.

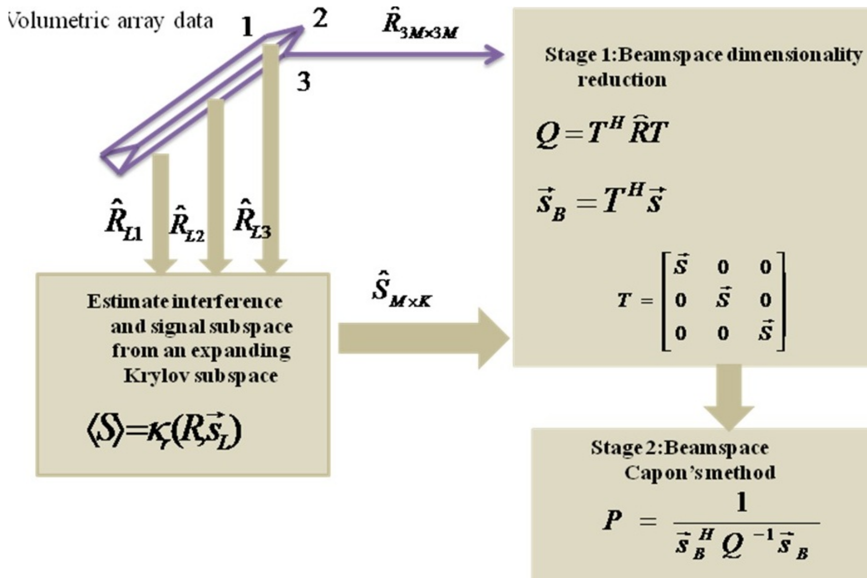

Figure 5: Block diagram of two stage Beam-Space and Sub-Array processing

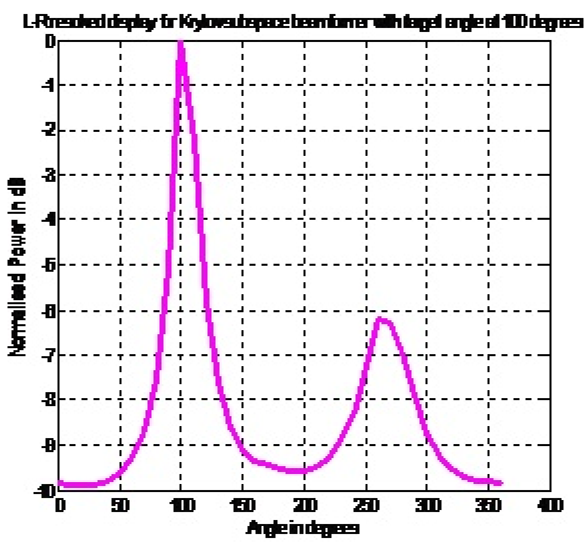

Figure 6: L-R resolved display of two stage Beam-Space and Sub-Array processing methods with target at $100\,\mathrm{deg}$

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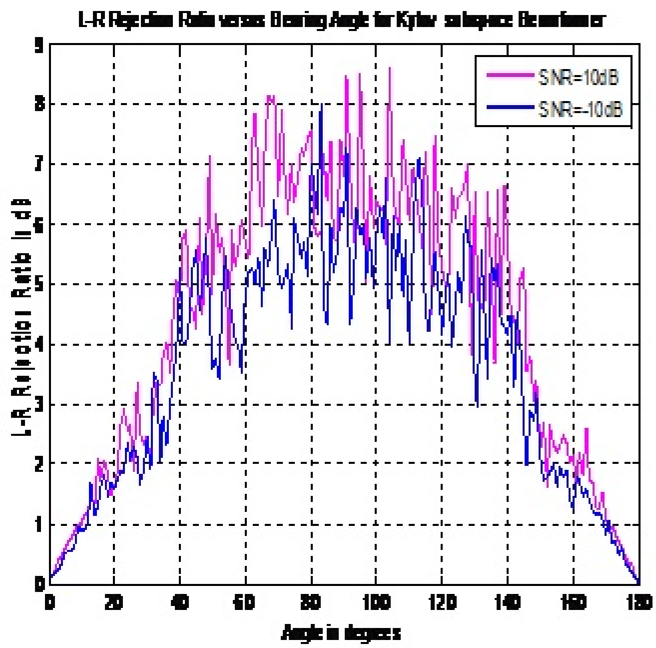

Figure 7: LRRR versus bearing angle for two stage Beam-Space and Sub-Array processing method

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