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ORIGINAL ARTICLE

Performance Analysis for Strong Interference Remove of Fast Moving Target in Linear Array Antenna

Kwan Hyeong Lee

Dept. Electriacal Electronic & Communicaton, Daejin University, 1007 Ho Guk ro, Pochen,Gyeonggi, Republic of KOREA

Abstract. This paper presents the performance analysis of direction of arrival estimation algorithm modified MUSIC algorithm. We present the description, comparison and the performance and high resolution analyses of these algorithms. The estimator is based upon a linear algebraic connection between the standard subspace model of the array correlation matrix and a special signal interference model. It is not a subspace weighted MUSIC because the scaling depends on the eigen-structure of the estimated signal subspace. Modified MUSIC algorithm has the advantage for simultaneously estimating the DOA and the power of each source. Estimate of the sampled channel impulse response is derived by use of the channel symbols. The channel response samples are separately processed to recover the DOA of the relative paths. Through simulation, we compare the DOA estimator with the modified MUSIC algorithm, based on these representations. Numerical results demonstrate the superior performance of modified MUSIC relative to general MUSIC and the validity of the results.

Keywords: DOA, MUSIC Algorithm, Eigen value, Array antenna.

1 INTRODUCTION

It is interesting to estimate the direction of arrival (DOA) parameters of signals in the noise background in such areas as communication, radar, sonar and geophysical seismology [1]. The well be known subspace based methods that dependent on the decomposition of the observation space into signal subspace and noise subspace, can provide high resolution DOA estimations with good estimation accuracy. However, the classical subspace based methods such as the MUSIC-type [2] methods, involve the estimate of the covariance matrix and its eigen decomposition. As a result, the classical subspace based methods are rather computationally intensive, especially for the case where the model orders in these matrices are large. Recently, the methods called reduced-order correlation kernel estimation technique and MUSIC algorithm [3] were presented to high-resolution spectral estimation which does not need the inverse of the covariance matrix The problem of using an antenna array to estimate the time delays and Doppler shifts (or frequency offsets) of a known signal is important in two common applications. First, in active radar and sonar, a known waveform is transmitted, and reflections from objects “illuminated” by the transmission are subsequently received. The received signals are often model scaled, delayed, and Doppler-shifted versions of the transmitted signal. Estimation of the signal amplitude, delay, and Doppler shift provides information about the position and relative motion of the objects. The second application involves estimation of the parameters of a multipath communication channel in situations where the transmitter is rapidly moving or has an unknown frequency offset. For example, consider a situation where a remote mobile user transmits a known waveform (e.g., a training sequence) to a base station for synchronization or equalization purposes. If the channel is frequency selective (nonzero delay spread), then the signal will be received with several distinct delays. In addition, due to the motion of the mobile and variations in the carrier frequency of the transmitter, the known signal can also be received with a small frequency offset. Estimation of the delays and frequency offsets, as well as the spatial signatures of the signal arrivals, is necessary in establishing a clean, inter symbol, and interference-free communication link. This paper presents a novel approach to solving the problems described above. The techniques presented are applicable in situations involving multiple antennas and, unlike classical methods, are asymptotically optimal at high SNR even when multiple overlapping copies of the signal are received. The frequency domain model used for time delay estimation is generalized to incorporate the presence of small frequency offsets. The resulting signal manifold in the frequency domain is shown to be a generalized version of the signal manifold of much the same way that polarization and local scattering generalize the standard array manifold in direction-of-arrival estimation. This observation motivates the development of subspace-based techniques similar to those in [4],[5], which provide closed-form solutions for the linear parameters (in our case, the frequency/Doppler offsets). Matched filtering techniques are known to be optimal in the maximum likelihood (ML) sense for a single signal arrival but are not consistent when multiple overlapping copies of the signal are present. While a number of authors have proposed time-delay estimators that exploit frequency domain data models, their use in Doppler estimation has not been widespread. When such models have been used, they have again only focused on the single signal path case. Other recently proposed techniques for the case of a single signal arrival include the wideband ambiguity function method and the structured covariance estimator. A recent paper [6] presents a de-convolution approach for resolving multiple delayed and Doppler shifted paths but only over a quantized parameter grid. The key features of the methods proposed below are that they provide continuous-valued estimates of time delays and Doppler shifts for multiple signal arrivals, and they are parametric estimators with asymptotic accuracy equivalent to that of the maximum likelihood approach. The outline of the paper is as follows. In the next section, we present time and frequency domain versions of the data model assumed in this work. By interchanging the roles of the samples in space and time, we show how the time delay and Doppler estimation problem can be cast in the well-studied framework of DOA estimation. In particular, we draw parallels between the array manifold in space that arises in DOA estimation and the signal manifold in time that we employ in this work. Under this paradigm, the classical matched filtering approach is seen to be equivalent to the simple delay-and-sum beamformer.

2 BEAMFORMUNG SIGNAL MODEL

Fig 1 is array antenna system. A representative member of the eigenvector methods is the MUSIC algorithm. However the presence of a highly correlated source, namely the target image, renders the conventional MUSIC in effective for low angle tracking over a smooth sea and air. We propose to extend MUSIC by replacing the direction of arrival search vector with the refined propagation model vector, here, the vector represents the wave front shape as sampled by the array geometry when specular multipath is present. In the conventional MUSIC, the DOA vector contains the classical exponentials representing the delay between the signal received by one sensor compared to a reference. In the MUSIC the vector is the mathematical description of the interaction between the direct and the indirect signals as seen by the array antenna. The presence of height ambiguities leads as to consider the simultaneous use of many frequencies in the bandwidth as in the exit algorithm. We derivation will follow closely the approach of Bienvenu[7], who has derived the form of the MUSIC estimator for multipath frequencies. We make the standard assumptions underlying the MUSIC algorithm, stationary process, known noise covariance matrix, the number of sources, less than the number of sensors, and the number of snapshots greater than the number of sensors. We consider here the case of snap shots or data vectors taken from an element array. The case where some or all frequencies are the same is included as a special case of the model. Because the properties of the eigenvector methods are derived for an infinite observation period. Performance for a finite approaches the ideal asymptotically as becomes large. We define a single observation vector, which is the concatenation of data snap shots observed at the array output at the intervals. Corresponding to this observation vector x_i, we defined a noise vector n_i, a signal vector s_i for the ith source, i=1 to P sources, and transfer matrix G_i from the signal source to the array outputs. The observation vector is then written as follows[8]

$$\text{X} = \sum_{i=1}^{P}(s_i G_i + n_i) \tag{1}$$

The deterministic matrix is the transfer matrix between the ith source and the signal component of the array output vector. The matrix contains the directional information on the source positions, the phase delay at the lth snapshot between the source and the array output signals. The covariance matrix is defined as follow

$$\text{R} = \text{E}\left[\{n_i n_i^H\} + \sum_{i=1}^{P} E\{G_i s_i s_i^H G_i^H\}\right] \tag{1}$$

$$= R_n + \sum_{i=1}^{P} G_i R_i G_i^H \tag{2}$$

The correlation matrix R_i is Toeplitz matrix since it is a stationary discrete time stochastic process. The matrix R_i may be diagonal by the singular value decomposition where the matrix Q_i that is used to diagonal R_i has as its columns an orthonormal set of eigenvectors for R_i. The resultant diagonal matrix ∇_i, has as its diagonal elements, the eigenvalues of R_i. We can be written

$$R_i = Q_i \, \nabla_i \, Q_i^H \tag{3}$$

It is quite difficult to fine analytically the eigenvalues and eigenvectors of a Toeplitz matrix. To circumvent that difficulty we use the fundamental theorem of [9] on the asymptotic behavior of the eigenvalue distribution of Toeplitz matrices. This theorem relates the properties of Toeplitz matrices to those of circular matrices. Circular matrices are an especially tractable class of matrices since the eigenvalues of such matrices can easily be found exactly as the discrete fourier transform of their first row and all circular matrices have the same set of eigenvectors. The eigenvalues of R_i are derived by construction an asymptotically equivalent circular matrix C_i as described in [10]. This is done using two criteria the strong norm and the weak known.

2.1 System Second order Signal Model

If we consider source to be the source of interest, then the signal noise ratio model may be written as the following signal interference noise model as follow[11]

$$y = A(\theta_i)\alpha_i + B(\theta_i)\beta_i + n \tag{4}$$

where Both $A(\theta)_i$ and $B(\theta)_i$ are the steering vector to source i[th] at angle θ_i, Both β_i and α_i are the complex amplitude of source and interference , respectively, and n is complex white noise of covariance. The steering matrix is$A = [A(\theta)_1, \cdots, A(\theta)_P]$. In this model, the steering matrix $B(\theta)_i = [B(\theta)_1, \cdots, B(\theta)_P]$ contains the $(P-1)$ interfering sources. The second order model from equation (4) can be written

$$R = E[yy^H] \tag{5}$$

$$= \sum_{i=1}^{P} s_i A(\theta_i)\, A^*(\theta_i) + \sigma^2 I \tag{6}$$

$$= ASA^* + \sigma^2 I \tag{7}$$

Where $S = \mathrm{diag}[s_1, \cdots, s_P]$ is the diagonal matrix of powers for the uncorrelated source. Each term $s_i a(\theta)_i a^*(\theta)_i$ is a rank-1 covariance matrix for a radiating source. The second order model can also be written to be from equation (4)

$$R = s_i\, A(\theta_i)\, A^*(\theta_i) + H_i B(\theta_i)\, B^*(\theta_i) + \sigma^2 I \tag{8}$$

Where $H_i = E[\beta\, \beta^*]$ is diagonal matrix of the interfering sources` powers. Equation(5) and (8) are model based representations for the measurement covariance matrix. Correlation matrix singular value decomposition can be written

$$R = [U_1 U_2] \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \sigma^2 I \end{bmatrix} \begin{bmatrix} U_1 \\ U_2 \end{bmatrix}^H \tag{9}$$

$$= U_1 \Sigma_1^2 U_1^* + \sigma^2 I \tag{10}$$

Where U_1 is the signal subspace, U_2 is the noise subspace. We denote the orthogonal projection matrices into the signal and noise subspaces by P_1 and P_2. P_1 denote the orthogonal projection matrix with signal range space. P_2 denote the orthogonal projection matrix with noise range space. Let us consider the least squares source separation of the component $A(\theta_i)\alpha_i$ from the measurement y

$$A(\theta_i)\, \hat{\alpha}_i = E[A(\theta_i)\, B(\theta_i) y] \tag{11}$$

$$= A(\theta_i)\, \left(A^*(\theta_i)\, P_2(\theta_i)\, A(\theta_i)\right)^{-1} A^*(\theta_i)\, P_2(\theta_i)\, y \tag{12}$$

The mean of $A(\theta_i)\, \hat{\alpha}_i$ is $A(\theta_i)\alpha_i$ and the second moment can be written

$$\mathrm{E}[\mathrm{A}(\theta_i)\hat{\beta}_i\hat{\beta}_i^*\ A^*(\theta_i) = E[A(\theta_i)B(\theta_i)](R_A + \sigma^2 I)E[A(\theta_i)B(\theta_i)]^* \tag{13}$$

When the angle between the subspace $\mathrm{A}(\theta_i)$ and $\mathrm{B}(\theta_i)$ is small, then the noise gain Trace $E[A(\theta_i)B(\theta_i)]E[A(\theta_i)B(\theta_i)]^*$ can be large. Equation(12) can be written again

$$E[A(\theta_i)B(\theta_i)(R_A - \sigma^2 I)E[A(\theta_i)B(\theta_i)]^* = A(\theta_i)s_i a^*(\theta_i) \tag{14}$$

The covariance for the interfering sources may be extracted as follow

$$E[A(\theta_i)B(\theta_i)(R_A - \sigma^2 I)E[A(\theta_i)B(\theta_i)]^* = B(\theta_i)H_i B^*(\theta_i) \tag{15}$$

Equation(14) and (15) can be combined to write

$$R_A = A(\theta_i)s_i a^*(\theta_i) + \ B(\theta_i)H_i B^*(\theta_i) \tag{16}$$

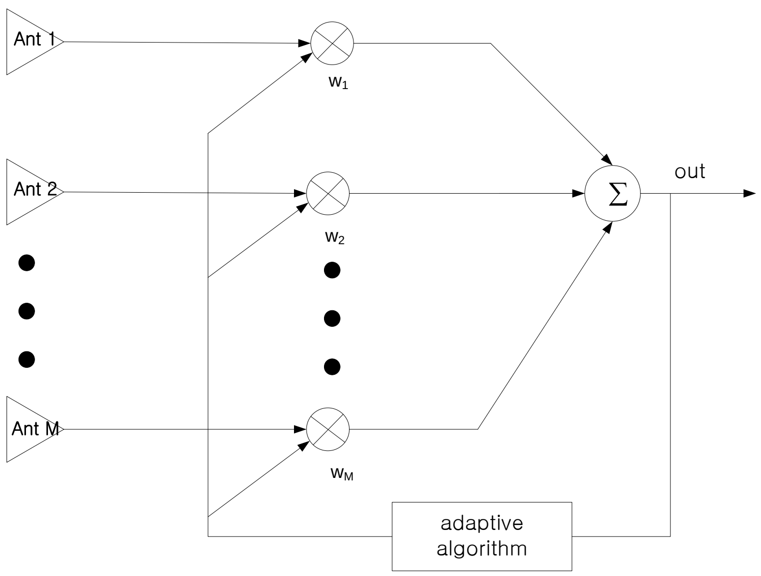

Figure. 1. Direction of arrival estimation with MUSIC algorithm

3 ESTIMATION OF SUBSPACE

3.1 Subspace Time Varying Channels

In this section, a second order analysis is carried out. Finite sample effects and calibration errors are not considered. Thus, only the effects of angular spreading are studied. The perturbation of the covariance matrix caused by the angular spreading is first related to the perturbation of the estimated signal and noise subspaces. These results are then used to find the perturbation of the estimated DOAs. For the case where the local scattering cause no angular spreading, but only variations of the received signal powers, $\nabla_i = 0$. The nominal covariance matrix of the observation, R is can be written

$$\mathrm{R} = A(\theta_i)s_i a^*(\theta_i) + B(\theta_i)H_i B^*(\theta_i) + \sigma^2 I \tag{17}$$

A basis for the nominal signal subspace may be defined from the eigenvalue decomposition of R

$$\mathrm{R} = E_s \Lambda_s E_s^* + E_I \Lambda_I E_I^* + E_n E_n^* \tag{18}$$

Where E_s, E_I, and E_n are signal, interference and noise subspace, respectively. The estimates calculated with this covariance matrix will coincide with the nominal DOAs. With angular spread, the sample covariance matrix can be written

$$\bar{R} = [A + \bar{A}]\Lambda\, S\, \Lambda^*[A + \bar{A}]^* + [B + \bar{B}]\Lambda\, S\, \Lambda^*[B + \bar{B}]^* + \sigma^2 I \tag{19}$$

The estimated basis for the nose subspace is defined from the eigenvalue decomposition of $\bar{R}$. The de-correlation between long observation period, to use the following approximation

$$B(\theta_i)\, B^*(\theta_i) \cong 0 \tag{20}$$

Note that the assumption of sequence de-correlation with co channel interference is basic for the derivation of the proposed method and that in practice this assumption is all the more valid if the training duration is long. Then, Equation(17) can be rewritten follow

$$\mathrm{R} = A(\theta_i)s_i a^*(\theta_i) + \sigma^2 I \tag{21}$$

3.2 DOA Estimation

The DOA are obtained as peaks in the following spectrum

$$P_i(\theta) = \frac{A(\theta)A(\theta)^H}{A(\theta)\ \left(I - V_i V_i^H\right) A(\theta)^H} \tag{22}$$

Where $\left(I - V_i V_i^H\right)$ denotes the orthogonal projector on the noise subspace relative to the ith sample of the channel response. In the case of uniform linear array, this search can be avoided by polynomial rooting. Here $V_i V_i^H$ is the orthogonal projector on the source subspace and V_i is obtained as the dominant eigenvector of R.

4 SIMULATION

We employ N = 6 sensor uniform linear array antennas with equal power signals arriving in half wavelength space. Output form these beams are all based on 50 snapshots. We assumed that there are uncorrelated signal sources all direction and equal power interferers all directional. In fig2, we see the response of the source, interference, and noise signal. In fig 3, we see the filtered signal on linear array antennas. In fig 4, we see that the graph is showed general MUSIC algorithm to estimate desired signal. It is a signal that we find desired signal. Fig 4 is showed estimation of 3 signals, and fig 4 is not correctly estimation not desired signal but estimation of 3 signals. In fig 5, we are showed application modified MUSIC algorithm proposed in this paper. Fig 5 is correctly estimation desired signal both interference and noise signal. We are showed an improvement that the proposed modified MUSIC algorithm in the estimation of the desired signal are better than the general MUSIC algorithm.

4 CONCLUSION

In this paper, we proposed modified MUSIC algorithm in order to desired signal estimator in wireless channel. We proposed the algorithm which is removal interference and noise signal in time impulse channel. The proposal algorithm is acquisition covariance matrix before removal noise and interference signal to find desired signal. We must find covariance matrix to divide as subspace to find desired signal. Subspace is divided signal and noise subspace. It is necessary to detect the number of sources before estimation of DOA. Modified MUSIC in this paper described here yields considerably superior performance as compared with the other MUSIC algorithm. The results of computer simulation showed that modified MUSIC algorithm is good performance better than general MUSIC method in order to find desired signal exiting interference and noise signal wireless communication.

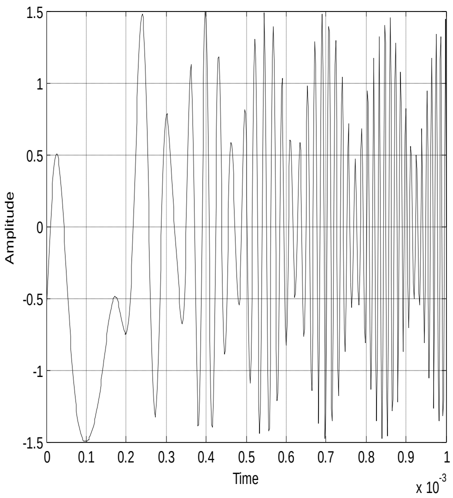

Figure. 2. Channel signal

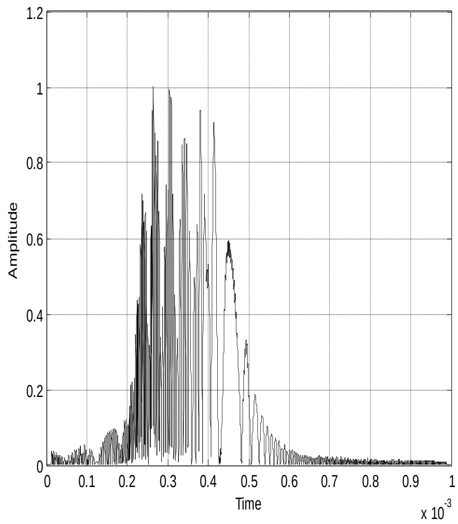

Figure. 3. Sampling Signal

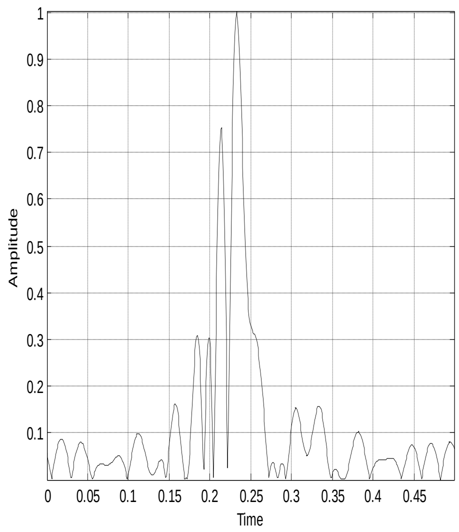

Figure. 4. General MUSIC signal

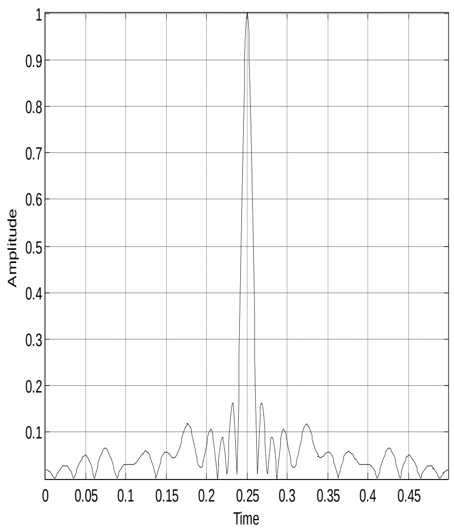

Figure. 5. Modified MUSIC signal

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