An Efficient Source Localization Method in Presence of Multipath using Smart Antenna System

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In this paper, a MATLAB based smart antenna testbed that efficiently localizes the line-of-sight (LOS) source in the presence of multipath signals is developed. By exploiting the consistent amplitude nature of the LOS signal, a variant of Constant Modulus Algorithm, namely Multitarget-Least Square Constant Modulus Algorithm is employed to adapt and update the weights of the smart antenna for estimation of the direction-of-arrival (DOA) of the of the LOS and multipath interference signals. Performance is compared with the conventional and recently proposed algorithms in the same testbed with alike considerations. Simulation result shows that the proposed method of DOA estimation performs better in terms of probability of resolution and root mean square error.

Introduction

Accurate source localization in a multipath environment always remains a challenge for researchers and engineers for decades. The perception of smart antenna, which uses an antenna array with an adaptive signal processor that can adjust its own beam pattern to put emphasis on signals of interest (SOI) and minimize signals, not of interest (SNOI) have aided to enhance direction finding capabilities and mitigate multipath interference. Blind adaptive algorithms always have advantages over non-blind counterparts, as the requisite training signal is not required, which reduces the spectral efficiency of the system. Constant Modulus Algorithm (CMA) proposed by Godard and later improved by Treichler and Agee[1] is a blind deconvolution iterative approach that inclines to preserve the envelope of the beam forming output at a nearly constant level, so it can separate the SOI from the SNOI. Least Square CM algorithm (LSCMA) that was proposed by Agee[2], uses the least square method and minimizes the cost function over a single block of data vectors which are updated on a block by block basis. Thus, LSCMA obtain faster convergence rate[3] and global stability as compared to conventional CMA.

In this paper, we make use of the Multi-target LSCMA (MT-LSCMA) based adaptive array system to estimate the direction-of-arrival (DOA) of the LOS source signal (SOI) in a multipath environment. A quasi-stationary source is assumed at the far-field region of the receiver smart antenna. MT-LSCMA exploits the constant amplitude property of the envelope of the narrowband received signals and extracts the SOI and suppresses the multipath (SNOI) or non-LOS (NLOS) signals by generating two sets of weights. Each set of weights selects one of the received signals as the SOI, rejecting the other as SNOI. This reduces the possibility of estimating a strong SNOI and rejecting an SOI, thus increasing the efficiency as compared to CMA and LSCMA.

A MATLAB testbed is proposed in this paper that uses MT-LSCMA based smart antenna system that adaptively updates the weights for source localization or DOA estimation of the LOS signal. Multipath interference (SOI or NLOS) signals are suppressed effectively. Performance is evaluated in terms of probability of resolution and root mean square error with the conventional MUltiple SIgnal Classification (MUSIC) algorithm as well as with recently proposed Modified-MUSIC (M-MUSIC)[4], and Normalized Least Mean Square (NLMS)[5] algorithms. Both M-MUSIC and NLMS have faster convergence rate with respect to their foundation methods of MUSIC and

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LMS algorithms.[6] While M-MUSIC uses block adaptation concepts, NLMS simply normalizes the adapted weight values. But NLMS, being non-blind adaptation method, requires a desired or training signal to develop the cost function.

Industry level development can be achieved with the proposed MATLAB testbed.

The rest of the paper is organized as follows. Section-II deliberates on the materials and methods (data model of DOA estimation) by an MT-LSCMA based adaptive array or smart antenna system. A brief mathematical outline is also stated for MUSIC, M-MUSIC and NLMS DOA estimation methods. In section-III, results and discussions (simulation results) of MATLAB testbed is projected. Performance comparison based on probability of resolution and root mean square error areaccomplished here. The paper is concluded by section-IV with conclusion.

Materials and Methods

Data Model for DOA Estimation

Basic notations used: N represents the total number of elements of the smart antenna. D signifies the number of narrowband signals, including the LOS (SOI) and NLOS (SNOI) that impinges on the array, while n indicates the iteration number. Bold letter symbols depict matrices or vector quantities. All other notations would be made familiar as and when essential. In Fig. 1 a uniform linear array (ULA) of a smart antenna consisting of Nsimilar and isotropic antenna elements, placed along the $y-$ axis with element spacing as $\lambda/2$ is depicted. RF signal generated by a source in the far field region, directly falls on the array with a DOA of θ_0, with constant amplitude. Multipath uncorrelated interference signals of the same source impinge on the array from various directions, $\theta_1, \theta_2, \dots\dots\dots\theta_m$ etc. It is assumed that the signals travel through an AWGN, frequency selective

Fig.1 — DOA estimation with LSCM array

channel that is homogenous and isotropic. Considering narrowband signal source, we can write the array input signal vector at the kth snapshot as:

$$x(\text{k}) = ABS_m(\text{k}) + n(\text{k}) \qquad \dots (1)$$

where $x(\text{k}) = [x_1, \dots\dots.x_N]^T$ is the received signal vector of the order of $N \times 1$. $A = A(\theta) = [a(\theta_0)\, a(\theta_1)\dots\dots a(\theta_m)]$ is the $N \times D$ array manifold matrix whose columns are $\{a(\theta_i)\}$, signifying the response of the array to a narrowband signal originating from a specific bearing. $B = diag(\beta)$ is the $D \times 1$ channel gain matrix with parameters $\beta = [\beta_0\, \beta_1\dots\dots \beta_m]^T$, where $\beta_i \in \mathbb{R}$ is the amplitude of the ith signal.

$S_m(k) = [s(k)i_1(k)\dots\dots i_m(k)]^T$ is the $D \times 1$ source vector with an overall D narrowband signals impinging on the array including the LOS source and its multipath components. It is assumed that $D \leq N$. $n(\text{k})$ is the AWGN vector with zero mean and variance as σ^2 and $\theta = [\theta_1 \dots\dots \theta_m]$ is the DOA vector of the impinging signals. $(.)^T$ represents vector transpose operation.

The CM array receives $x(k)$ and form blocks of data vector as $X = [x(1)\dots\dots.x(p)]$ where $p$is the number of data samples in each block. As an alternative of directly estimating the correlation matrix R_x, it estimates $S_i(k)$ of $S_m(k)$ and source direction vector a_i in a block iterative process and hence the angle of arrival θ_i. From Fig. 1, the output of the weight-and-sum beam former is given by:

$$y(k) = w^H(k)X(k) \qquad \dots (2)$$

where $w(k) = [w_1(k)\dots\dots w_N(k)]^T$ are the adaptive weights accustomed by MT-LSCM algorithm and $(.)^H$ is the Hermitian transpose. To determine the adaptive weights, the dynamic nonlinear least-square CM optimizes $\min_{w^* S}\|w^*X - S\|$ $s.t$ $|S_i(t)| = 1$ $t = 1, \dots\dots N$ where $\|.\|$ is the vector $2-$norm. The minimization is achieved by projecting w^*X into the set of constant modulus signals through dividing entry-wise by modulus by means of the projection operator $r(S) = \left[\frac{S(1)}{|S(1)|} \dots \dots \frac{S(n)}{|S(n)|}\right]$, where n is the number of iterations. Finally, we can optimize over $w$and find the least square solution as $w^* = SX^\dagger$, where $\dagger$ denotes the Moore-Penrose pseudo inverse. Given an initial point $w^{(0)}$, the value of the weights updated by block iteration is given by:
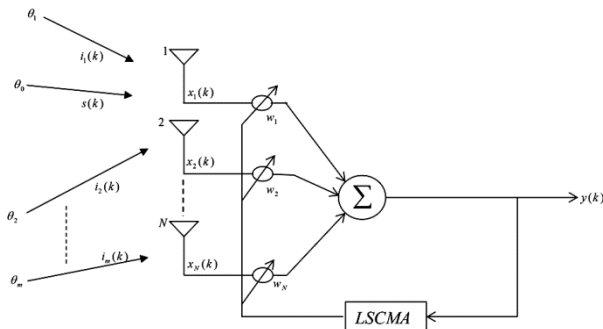
$$S^{(n+1)} = r(S)\left(w^{(n)*}X\right)$$
$$w^{(n+1)} = S^{(n+1)}X^{\dagger} \qquad \qquad \dots (3)$$

The weight updating calculation of MT-LSCMA is given by Eq. (3). In a changing environment, the data blocks are updated for each iteration, resulting in dynamic MT-LSCMA. The iterations continue until appropriate convergence is satisfied. Characteristically, this is somewhat similar to the Sample Matrix Inversion (SMI) algorithm.[7,8]

The summary of the proposed method is provided below in Table 1.

For the conventional MUSIC algorithm, we use the array correlation matrix from equation (1) as $R_{xx} = AR_{ss}A^H + R_{nn}$ where R_{ss} is the $D \times D$ source covariance matrix and R_{nn} is the $N \times N$ noise correlation matrix. MUSIC, being a subspace based method, performs eigenvalue decomposition of R_{xx} and estimates signal and noise subspace (E_S and E_N respectively) from $\hat{R}_{xx}$. Finally, the spectrum $[a(\theta)^H E_N E_N^H a(\theta)]^{-1}$ is calculated w.r.t θ to estimate D number of peaks from the pseudospectrum.

In M-MUSIC algorithm, as proposed by Liu *et al*.[4] a new array correlation matrix $R_{xxN'}$ is formed from randomly chosen N' elements from N for $N' < N$. Next, Nyström approximation is employed for estimation of noise subspace, $E_{N'}$. After this, the procedure continues in a similar approach as MUSIC in estimating DOA angle θ.

Table 1 — DOA estimation procedure of the proposed method

1. Receive k snapshots of x(k)
2. Form the block sets $X = [x(1) \dots \dots x(p)]$
3. Establish the weight update vectors of MT-LSCMA by using equation (3) and estimate the manifold matrix $A = [a(\theta_1) \dots \dots a(\theta_m)]$
4. For each column vector $a(\theta_i)$ of A, estimate $\hat{\theta}_i$ from the peaks of the plot. The projection of 1D of each a_i into the array steering matrix is given by:
$$\hat{\theta}_i = argmax_\theta \frac{\hat{a}_i^* a(\theta)}{\|a(\theta)\|}$$

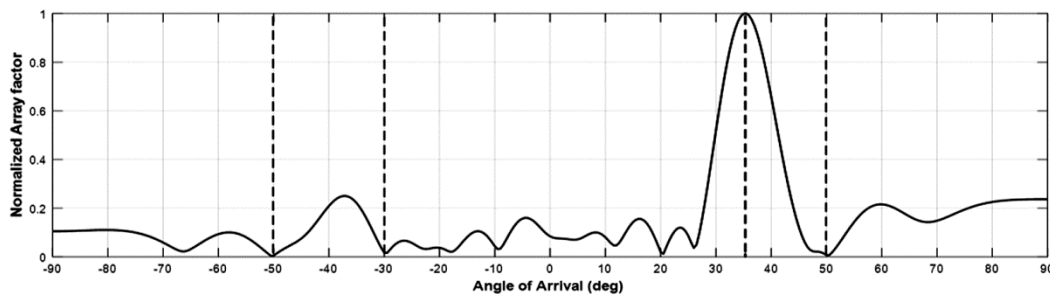The NLMS algorithm for DOA estimation, as proposed by Bakhshi and Shahtalebi[5], uses a training or desired signal d to minimize the mean square error (MSE) with the output of the array in an iterative, normalized updating. The DOA angle is estimated by optimizing
$$\theta = \frac{argmax}{\theta}\{\|\hat{a}(\theta)|_n\|\}, \quad \text{where } \|\hat{a}(\theta)|_n\| \text{ is the}$$
norm of the weight estimates and n is the total number of iterations.

Results and Discussion

Simulation Results

A MATLAB based testbed of smart antenna is designed where we inspect the performance of the proposed method and compare with the established schemes of source localization/DOA estimation, namely MUSIC, M-MUSIC and NLMS. The experiments are carried out in MATLAB R2018, on a laptop based on Intel (R) Core (TM) i7-8656U CPU @ 4.6 GHz and 8 GB RAM. The system type is 64-bit operating system-Microsoft Windows 10 Home edition. A 3 GHz signal is generated in the far field of an $16 -$ element ULA based receiver, whose antenna element spacing is fixed at $\frac{\lambda}{2} = 0.005\,m$. This narrowband signal, having constant amplitude, is the LOS (or SOI) that impinges on the ULA at an angle of 35°. Three multipath interfering signals constituting NLOS (or SNOI) arrive at the ULA from ±50° and −30°.

The number of snapshots is considered to be $k = 10$. The block length of MT-LSCMA is assumed to be $p = 130$. For M-MUSIC, $N' = 8$ and for NLMS, the step size is set at $\mu_{NLMS} = 0.1$. The DOAs are expected to be random variables with uniform distribution over (−90°90°). Considering AWGN, the SNR is varied between −15 dB to 15 dB.

A plot of the variation of a normalized array factor (in dB) with DOA of the proposed method at $SNR = 0\,dB$ is given in Fig. 2. The vertical dotted line at 35°

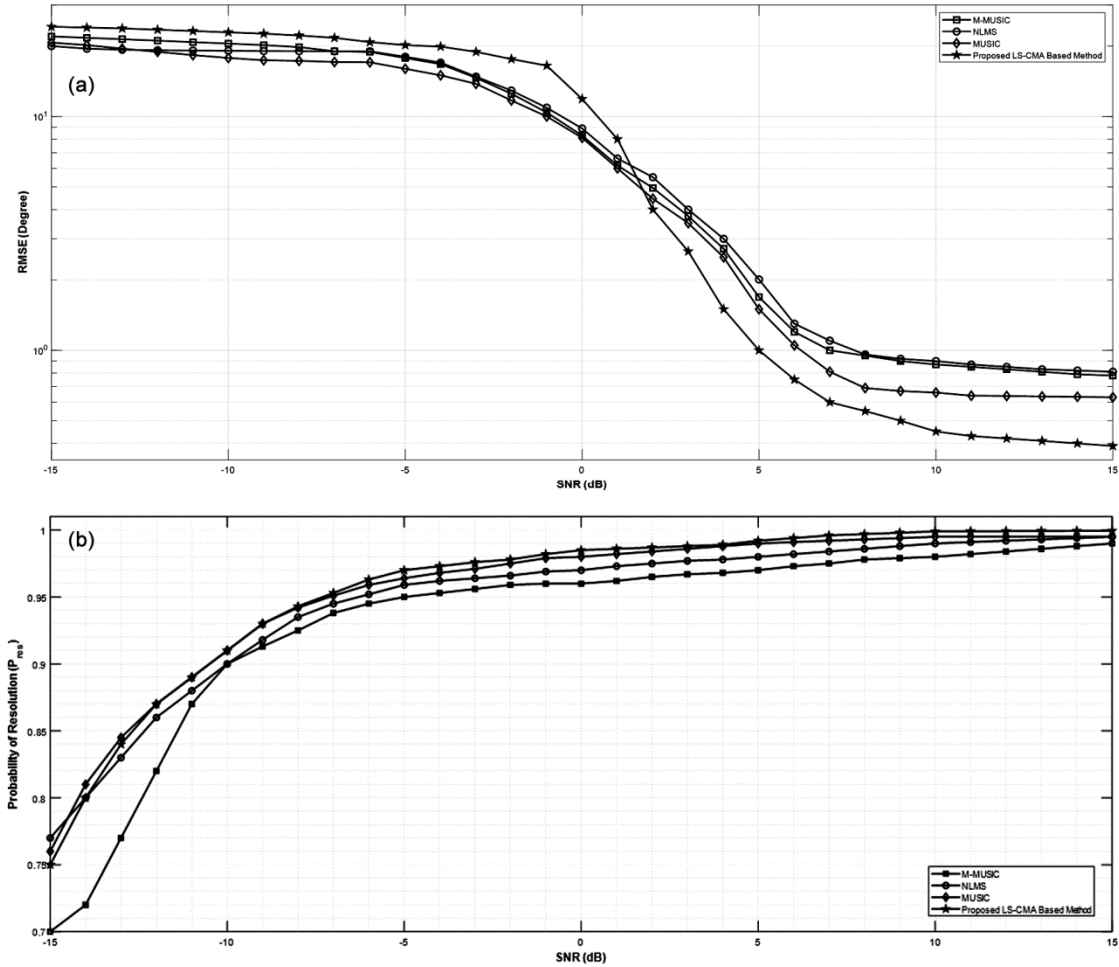Fig. 2 — Variation of normalized AF with DOA angles at SNR = 0 dB

Fig. 3(a-b) — (a) Variation of RMSE of DOA estimation with SNR and (b) Variation of P_res with SNR

(angle of arrival) indicates the LOS source and the other vertical dotted lines specify the multipath interference signal directions. The interference locations are suppressed considerably while the direction of the LOS has high value of normalized AF (Fig. 2).

Now we compare this method with MUSIC, M-MUSIC and NLMS in terms of probability of resolution (P_{res}) and root mean square error (RMSE) of the estimated DOA of the LOS signal. We define probability of resolution as follows[8]

$$P_{res} = Prob\left\{\left|\hat{\theta}_i - \theta_i\right| \leq \frac{\Delta\theta}{2}\right\}, i = 1......m,$$

where $\Delta\theta = \min\{|\theta_{i1} - \theta_{i2}|, 1 \leq i_1 \leq i_2 \leq m\}$.

The RMSE for Q number of Monte Carlo trials is given as below[8]

$$RMSE = \sqrt{\frac{1}{Qm}\sum_{q=1}^{Q}\sum_{i=1}^{m}(\hat{\theta}_i - \theta_i)^2},$$ assuming

$Q = 1000$ trials. The same experimental parameters of DOAs of the LOS and NLOS signals are fixed.

The variation of RMSE with SNR varied between $\pm15\,dB$ with steps of $1\,dB$ as shown in Fig. 3a. The plot clearly depicts that the proposed method outperforms the other methods as SNR increases. M-MUSIC and NLMS almost have the same performance over the total SNR range while MUSIC, like the proposed method has improved performance at higher SNR values. The variation of P_{res} with SNR in the same range with steps is given in Fig. 3b. The proposed method shows slightly better resolution than MUSIC and NLMS as SNR increases, while the resolution ability of M-MUSIC in the same SNR range remains inferior.

Conclusions

A MATLAB testbed is proposed in this paper for efficient DOA estimation or source localization of a smart antenna system in presence of interfering multipath signals. Multi-target LSCM algorithm

exploits the constant amplitude property of the line-of-sight signal in the multipath scenario and efficiently locate the source direction while suppressing the multipath signals received by the adaptive array of smart antenna. Simulation results in resolution and root mean square error versus SNR (dB) clearly shows that the proposed method performs better thanthe conventional MUSIC algorithm and newly developed M-MUSIC and NLMS algorithms at considerable SNR values. Lower computational complexity can be achieved as sub-space based decomposition can be avoided as in MUSIC and M-MUSIC. In addition, higher spectral efficiency can be accomplished as compared to NLMS as constant modulus based algorithm do not require training or desired signal to adapt the weights. Block adaptation correspondingly involves a lesser number of iterations to achieve global minima, making it a fast estimation process. The MATLAB based testbed can be extended for the development of industry level smart antenna system.

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