A Novel DOA Estimation Methodology Utilizing Null Steering Antenna Algorithm

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***Abstract*—Past decades have seen significant advances in array signal processing and its applications. Direction of Arrival (DOA) estimation is one the most significant application of antenna arrays. This paper presents a new direction-of-arrival (DOA) estimation methodology, where DOA estimation is realized by the nulling antenna algorithm. The new methodology aims to minimize the computational complexity while maintaining high degree of accuracy and resolution. Unlike the existing MUSIC algorithm, the proposed algorithm eliminates the need of estimating the number of signals and the eigenvalue decomposition of covariance matrix, thereby avoiding performance deterioration caused by incorrect source number estimation. Both the theoretical analysis and computer simulations show that the proposed method outperforms the conventional techniques in estimating DOA of signals while having less computational complexity and high resolution.**

***Index Terms*—DOA Estimation, Adaptive Filtering, Spatial Filtering, Power Inversion, Array Signal Processing.**

I. Introduction

DOA estimation is a prominent figure in the field of array signal processing applied in satellite navigation systems, radars, sonars, seismic and mobile communication systems [1-3]. The principal thrust of the research in array signal processing over the last decade has been directed towards DOA estimation. The reason behind this widespread interest is the motivation by the tremendous popularity of the null steering antenna, which emerged as a key technology to accomplish the striving requirement of enhanced range and capacity [1-5].

There are many applications where the sole focus is the precise estimation of a signals direction of arrival (DOA). Radar, sonar, and mobile communication systems are not all but few examples of many possible applications. DOA methods are utilized for designing and adapting of the directivity of antenna arrays. For example, an antenna array can be designed to accept signals from some specific directions, while rejecting signals from all other directions by declaring them as interference. [6]

In lots of DOA estimation algorithms with excellent performance, MUSIC is one of the leading super resolution algorithm that has attracted attention in past two decades [7-8]. However, due to the fact that MUSIC algorithm needs the estimate of the number of sources and the Eigen-value decomposition of the covariance matrix of the received signal, the implementation of these operations in FPGA or DSP devices are more difficult and expensive [9-10]. So a new algorithm has been derived to achieve DOA estimation utilizing null steering antenna and spatial filtering algorithm to eradicate the limitations in MUSIC algorithm. The new algorithm works well for any kind of geometry of antenna array.

The remaining paper is structured as follows. Section 2 introduces the basic concept of nulling antenna in adaptive filtering by elaborating on the signal model and adaptive filtering algorithm. Section 3 covers the proposed methodology of DOA estimation algorithm based on adaptive filtering. Section 4 discusses the performance analysis of the proposed algorithm in detail. The simulation results of the proposed algorithm are given in section 5. Finally section 6 offers some conclusions drawn on the basis of simulation results.

II. Narrowband Null Steering

The two basic approaches to spatial filtering that are directly applicable to Direct Sequence Spread Spectrum (DSSS) systems are null Steering and beamforming. Null steering approaches require minimal knowledge of the desired signal and are generally easier to implement than beamforming.

Narrowband null steering is the simplest spatial filtering approach. The basic idea is to simply place nulls in the direction of the interference signals. This approach is depicted in Fig. 1:

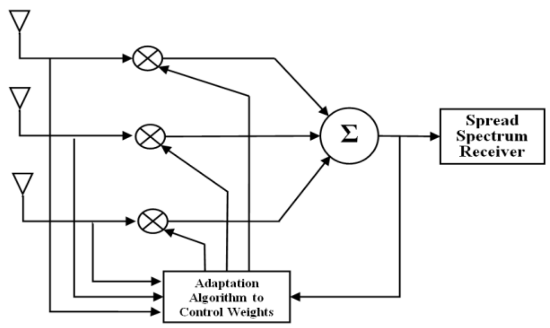

Fig. 1. Narrowband Null Steering.

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The antenna pattern typically is initially configured as an omni-directional pattern. Other initial patterns are possible and are determined by the initial beam steering vector. For example, the initial beam steering vector may be configured to mask off low elevation angles and jammers generally arriving from lower elevation angles. The adaptive algorithm modifies the complex antenna weights to minimize the power at the output of the antenna summing junction. This results in nulls in the antenna pattern in the direction of the undesired signals provided that jamming signal is stronger than the desired signal. This approach works best when the desired signal is well below the noise floor. If the desired signal is not well below the noise floor, this approach would null the desired signal. For many DSSS systems this is not an issue since the DSSS signal is well below the noise floor. Compton gives an excellent example of this approach in [11]. This method can be also used for DOA estimation to cop up the shortcomings of the MUSIC algorithm and classical Delay-and-Sum method.

A. Signal Model

Assume a uniform linear array (ULA) with N+1 elements, where the first 0-based array element is located at the origin of the coordinates, and the remaining N elements represents auxiliary array. Let the signal incident on the main array element represent the reference signal which is given by:

$$x_0(k) = s_0(k) + \sum_{m=1}^{M} s_m(k) + n_0(k) \tag{1}$$

where $s_0(k)$ is the desired signal, $s_m(k)$ are the M interference signals, given that $m = 1,2,3,\cdots,M$ and $n_0(k)$ is the noise. Assuming that the interference signal and desired signal are narrowband signals at the same frequency and the spacing between the adjacent elements of the array is half-a-wavelength, the signal received at the auxiliary array is:

$$\boldsymbol{x}(k) = \begin{bmatrix} x_1(k) \\ \vdots \\ x_N(k) \end{bmatrix} = s_0(k)\boldsymbol{v}(\theta_0) + \sum_{m=1}^{M} s_m(k)\boldsymbol{v}(\theta_m) + \boldsymbol{n}(k) \tag{2}$$

where $\boldsymbol{v}(\theta_0)$ and $\boldsymbol{v}(\theta_m)$ are the array steering vectors of the desired and m-th interference signal respectively, which depend on the values of the DOA θ_0 and θ_m of the desired and interference signals.

In fact, the desired signal conducted by the null steering antenna is weak and the wireless environment such as the satellite navigation system experiences strong signal interference. The desired signal due to the impact of spread spectrum modulation in the above received signal model is far less than the noise [12]. Therefore, (1) can be simplified to:

$$x_0(k) = \sum_{m=1}^{M} s_m(k)\boldsymbol{v}(\theta_m) + \boldsymbol{n}_0(k) \tag{3}$$

Consider the vector array of the signal model:

$$\boldsymbol{x}(k) = \begin{bmatrix} x_1(k) \\ \vdots \\ x_N(k) \end{bmatrix} = \sum_{m=1}^{M} s_m(k)\boldsymbol{v}(\theta_m) + \boldsymbol{n}(k) \tag{4}$$

B. Adaptive Filtering Algorithm

In satellite navigation applications, power inversion adaptive filtering method has the configuration shown in Fig. 2 [13]. The main array element receives a signal $x_0(k)$ as the reference signal while the auxiliary array element receives a signal $\boldsymbol{x}(k)$ using the power inversion criterion [14], in order to get the least mean square error between the weighted sum of the signal and the reference signal, which is called the cost function:

$$J(\boldsymbol{w}) = E[e(k)e^*(k)] \tag{5}$$

which has a minimum value, where the error $e(k)$ is defined as:

$$e(k) = x_0(k) - \boldsymbol{w}^H(k)\boldsymbol{x}(k) \tag{6}$$

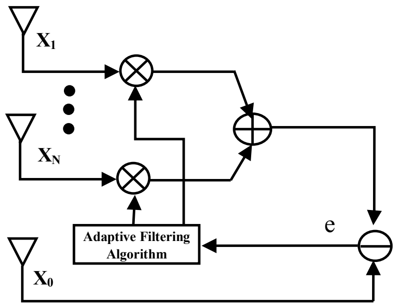

Fig. 2. Structure of spatial filter

According to the study of basic theory of adaptive filtering [15], the optimal (Wiener) solution is given by

$$\boldsymbol{w}_{opt} = \boldsymbol{R}^{-1}\boldsymbol{p} \tag{7}$$

where

$$\boldsymbol{R} = E[\boldsymbol{x}(k)\boldsymbol{x}^H(k)] = \sum_{m=1}^{M} \sigma_m^2 \boldsymbol{v}(\theta_m)\boldsymbol{v}^H(\theta_m) + \sigma_n^2 \boldsymbol{I} \tag{8}$$

$$\boldsymbol{p} = [\boldsymbol{x}(k)x_0^*(k)] = \sum_{m=1}^{M} \sigma_m^2 \boldsymbol{v}(\theta_m) \tag{9}$$

$\boldsymbol{R}$ is the covariance matrix of the received signal, $\boldsymbol{p}$ is cross-correlation vector of the received signal with the reference signal, σ_m^2 is the power of m-th interference signal, and σ_n^2 is the noise power.

In the LMS algorithm, the covariance matrix (***R***) and the cross correlation vector (***p***) are replaced by their instantaneous values.

In the Wiener solution case, the minimum mean square error is given by:

$$J_{\min} = J(\boldsymbol{w}_{opt}) = \sigma_0^2 - \boldsymbol{p}^H \boldsymbol{R}^{-1}\boldsymbol{p} \tag{10}$$

where, σ_0^2 is power of reference signal.

In case of using LMS algorithm [16], weighted iteration method is:

$$e(k) = x_0(k) - \boldsymbol{w}^H(k)\boldsymbol{x}(k) \tag{11}$$

$$w(k+1) = w(k) + \mu x(k)e^*(k) \tag{12}$$

The basic idea of the above algorithms is that, if the interference signal have a larger interference-noise ratio, and the desired signal is small, the error $e(n)$ is the output signal after interference is been eliminated. Consider all N+1 elements as a new antenna array, and $e(n)$ is the output signal of the system, the weight vector and the direction vector are equivalent to:

$$\boldsymbol{w}_e = \begin{bmatrix} 1 \\ -\boldsymbol{w} \end{bmatrix} \tag{13}$$

$$\boldsymbol{\upsilon}_e(\theta) = \begin{bmatrix} 1 \\ -\boldsymbol{\upsilon}(\theta) \end{bmatrix} \tag{14}$$

After convergence of the weight vector based on the adaptive filter theory, the array Pattern is:

$$B(\theta) = \boldsymbol{w}_e^H \boldsymbol{\upsilon}(\theta) \tag{15}$$

Since the input signal consist of only interference and noise, so it form nulls in the spatial spectrum which only appears in the interfered DOA zone, while the remaining angles are relatively flat.

III. Proposed Methodology

The DOA's of multiple incident signals can be estimated according to the preceding section, which introduces the adaptive spatial filtering based on nulling antenna. Use iterative equations (11) and (12) to compute the weight vector until the algorithm is converged. The new weight vector is formed according to (13). The convergence factor μ used in (12) should be chosen in a specific range to guarantee convergence of the weight vector. This is discussed briefly in the upcoming sections.

According to (15) nulls are placed in the DOA of signals only, so the spatial spectrum for DOA estimation can be defined as a reciprocal of (15) and can be defined as:

$$P(\theta) = \frac{1}{|B(\theta)|} = \frac{1}{\boldsymbol{w}_e^H \boldsymbol{\upsilon}_e(\theta)} \tag{16}$$

Clearly, the nulls in the reciprocal of spatial spectrum will appear as spectral peaks and peak positions are the estimated DOA of the signal.

Thus, the proposed DOA estimation algorithm does not require a prior estimation of the number of sources, which avoid performance degradation when the numbers of sources are over-estimated or under-estimated as in MUSIC algorithm. Moreover, the computational complex process of Eigen-value decomposition is also eliminated in case of proposed algorithm.

The implementation of the proposed algorithm is summarized as follows.

TABLE I
SUMMARY OF THE PROPOSED ALGORITHM

Implementation steps of proposed algorithm	
1)	*Parameters*: N = number of sensors μ= step-size $0 \le \mu \le \frac{2}{\lambda_{max}}$ where λ_{max} is the maximum eigenvalue of $\boldsymbol{R}$.
2)	*Initialization*. If prior knowledge about the weight vector $\boldsymbol{w}(k)$ is available, use that knowledge to select an appropriate value for $\boldsymbol{w}(0)$. Otherwise, set $\boldsymbol{w}(0) = 0$.
3)	*Data* Given: $x_n(k)$ = N+1-by-1 tap input vector at time *k*, where $n = 0,1,\ldots,N$ $x_0(k)$ = reference signal.
4)	To be computed: $\boldsymbol{w}(k+1)$ = estimate of tap-weight vector at time step *k + 1*. *Computation*: For *k* = 0, 1, 2, . . . , compute $e(k) = x_0(k) - \boldsymbol{w}^H(k)\boldsymbol{x}(k)$, $w(k+1) = w(k) + \mu x(k) e^*(k)$.
5)	Form a new weight vector $\boldsymbol{w}_e$ according to equation (13);
6)	Compute the spatial spectrum based on (16).

IV. Performance Analysis

A. Stability Analysis

Stability of the LMS algorithm is an important performance metric. Here, we analyze the conditions for the stability of the LMS algorithm. The close form for the MSE learning curve of the LMS algorithm for small μ can be expressed as [17]:

$$J(k) = J_{\min} + \mu J_{\min} \sum_{n=1}^{N} \frac{\lambda_n}{2 - \mu\lambda_n} + \sum_{n=1}^{N} \lambda_n \left[|\upsilon_n(0)|^2 - \frac{\mu J_{\min}}{2 - \mu\lambda_n} \right] (1 - \mu\lambda_n)^{2k} \tag{17}$$

where λ_n is the $n-th$ eigenvalue of the covariance matrix $\boldsymbol{R}$, and $\boldsymbol{\upsilon}_n(k)$ is the instantaneous covariance matrix and the error determines the instantaneous value of the weight vector [18].

Equation (17) represent the mean-square error produced by the LMS algorithm for small μ compared to the permissible limit $2/\lambda_{\max}$.

Equation (18) gives the sufficient condition for the convergence of the proposed algorithm, which is the value of the step size μ and it should be:

$$0 \le \mu \le \frac{2}{\lambda_{\max}} \tag{18}$$

This condition does not ensure the stability of the LMS algorithm, instead it guarantees the convergence of the algorithm. The MSE does not exactly converge to $J_{\min}$ due to the oscillations. To characterize this property in steady state, a new measurement referred to as the misadjustment for small μ is defined as

$$\mathcal{M}=\frac{\sum_{n=0}^{N-1}\frac{\mu\lambda_n}{1-2\mu\lambda_n}}{1-\sum_{n=0}^{N-1}\frac{\mu\lambda_n}{1-2\mu\lambda_n}} \tag{19}$$

Where

$$\sum_{n=0}^{N-1}\frac{\mu\lambda_n}{1-2\mu\lambda_n}\approx\mu\sum_{n=0}^{N-1}\lambda_n=\mu\mathrm{Tr}(\boldsymbol{R}) \tag{20}$$

So we get

$$\mathcal{M}=\frac{\mu\mathrm{Tr}(\boldsymbol{R})}{1-\mu\mathrm{Tr}(\boldsymbol{R})} \tag{21}$$

When $\mathcal{M}$ is sufficiently small, $\mu\mathrm{Tr}(\boldsymbol{R})$ can be ignored it in the denominator in order to obtain

$$\mathcal{M}=\mu\mathrm{Tr}(\boldsymbol{R}) \tag{22}$$

This new refined formula predicts the misadjustment more accurately. For small values of μ , it is identical to the original formula.

From the above analysis we can conclude that the step-size parameter governs the convergence speed of the LMS algorithm. Large step-size μ speeds up the convergence of the algorithm, while it reduces the precision of the steady-state solution of the algorithm as from (22). Therefore, the algorithm has a trade-off between the convergence speed and the misadjustment.

B. Computational complexity

Computational complexity of the proposed algorithm comprises of the iterative calculations of the weight vector and the spatial spectrum calculation. Eq. (17) shows that the evolution of the mean-square error is governed by the exponential factor $(1-\mu\lambda_n)^{2k}$. If the time constant τ is used to define the number of iterations required for the amplitude of $J(k)$ to decay to $1/e$ of its initial value, we can approximate τ for small μ as

$$\tau=\frac{-1}{2\ln(1-\mu\lambda_{\min})} \tag{23}$$

Therefore, the LMS algorithm has N time constants corresponding to its N eigenvalues. The exponential factors corresponding to large eigenvalues decrease to zero fast, whereas small eigenvalues slow down the overall convergence.

The algorithm weights are updated according to (11) and (12), each iteration requires two times complex multiplication and addition respectively, so the number of multiplications and additions is defined as:

$$2\tau=\frac{-1}{\ln(1-\mu\lambda_{\min})}\approx\frac{1}{\mu\lambda_{\min}} \tag{24}$$

While in computation of spatial spectrum, each search angle will be calculated by equation (16). Since the first element in the weight vector and the direction vector is a constant 1, so one iteration of the proposed algorithm requires N multiplications and N additions for the weight updating and error generation. The number of computations depends on the search step $\Delta\theta$, then for linear array the number of computations requires to estimate the spatial spectrum is $\pi N/\Delta\theta$.

Combining the two computations, multiple numbers of multiplications and additions required by the algorithm is $\frac{1}{\mu\lambda_{\min}}+\frac{\pi N}{\Delta\theta}$.

In contrast to MUSIC algorithm, the proposed algorithm requires iterative computations, which makes it less complex. On the other hand, the MUSIC algorithm performs the eigen-decomposition of the covariance matrix and also requires the estimate of the number of sources. These operations make the MUSIC algorithm more complex and hard to implement in real-time applications.

C. Error estimation

The ensemble-average learning curve of the LMS algorithm does not exhibit oscillations, rather it decays exponentially to the constant value. When the number of iterations tends to infinity, the third term is zero in (17) and the error of the filter is equal to

$$J(\infty)=J_{\min}+\sum_{n=1}^{N}\lambda_n\frac{\mu J_{\min}}{2-\mu\lambda_n} \tag{25}$$

$$J(\infty)=J_{\min}(1+\mu\sum_{n=1}^{N}\frac{\lambda_n}{2-\mu\lambda_n})=J_{\min}\cdot\xi \tag{26}$$

Whereas, the signal and noise power determine the characteristic value, i.e.

$$\lambda_n=\begin{cases}\sigma_m^2+\sigma_n^2, n=m=1,2,\cdots,M\\ \sigma_n^2, n=M+1,\cdots,N\end{cases} \tag{27}$$

For small step size, the MSE is given by

$$\xi=(1+\frac{\mu N\sigma_n^2}{2}+\mu\sum_{m=1}^{M}\frac{\sigma_m^2}{2}) \tag{28}$$

The inverse of covariance matrix in (8) by matrix inversion can be derived as

$$\boldsymbol{R}^{-1}=\frac{1}{\sigma_n^2}\boldsymbol{I}-\frac{1}{\sigma_n^2}\sum_{m=1}^{M}\frac{\sigma_m^2}{N\sigma_m^2+\sigma_n^2}\boldsymbol{v}(\theta_m)\boldsymbol{v}^H(\theta_m) \tag{29}$$

Substituting (9) and (29) into (10) and considering the spatial orthogonality between the signals produces:

$$\begin{aligned}J_{\min}&=\sigma_0^2-\mathbf{p}^H\mathbf{R}^{-1}\mathbf{p}=\sigma_n^2+\sum_{m=1}^{M}\frac{\sigma_m^2\sigma_n^2}{N\sigma_m^2+\sigma_n^2}\\&=\sigma_n^2+\sum_{m=1}^{M}\frac{\sigma_m^2}{N\frac{\sigma_m^2}{\sigma_n^2}+1}\end{aligned} \tag{30}$$

Equations (28) and (30) show that the array output error in the LMS algorithm increases as the signal power or the noise power increases, while the output error can be reduced by enhancing the SNR.

D. Resolution Performance

Since the optimal weight vector is theoretically equal to the Wiener solution, the spatial spectrum can be expressed by substituting (7) into equation (16) as:

$$p(\theta)=\left|\frac{1}{1-\mathbf{p}^{H}\mathbf{R}^{-1}\boldsymbol{\upsilon}(\theta)}\right| \tag{31}$$

For any two spatial incident signals θ_{m1} and θ_{m2}, the condition for distinguishing is given as:

$$p(\frac{\theta_{m1}+\theta_{m2}}{2})\langle\frac{p(\theta_{m1})}{p(\theta_{m2})} \tag{32}$$

Let $\sigma_{m1}^2>\sigma_{m2}^2$, then:

$$\mathbf{p}^{H}\mathbf{R}^{-1}=\sum_{i=1}^{M}\frac{\sigma_{mi}^2}{N\sigma_{mi}^2+\sigma_n^2}\boldsymbol{\upsilon}^{H}(\theta_{mi}) \tag{33}$$

Inequality is

$$\sum_{i=1}^{2}\frac{\sigma_{mi}^2}{N\sigma_{mi}^2+\sigma_n^2}\boldsymbol{\upsilon}^{H}(\theta_{mi})\boldsymbol{\upsilon}(\theta_{m1}+\frac{\Delta\theta}{2})<\frac{N\sigma_{m2}^2}{N\sigma_{m2}^2+\sigma_n^2} \tag{34}$$

Since the array steering vector is defined as:

$$\boldsymbol{\upsilon}^{H}(\theta)=[e^{j\pi\sin\theta},\quad\ldots\quad e^{jN\pi\sin\theta}] \tag{35}$$

Substituting inequality, we have:

$$\left|1-pa-qa^{H}\right|>\left|1-pb-qN\right| \tag{36}$$

where

$$p=\frac{\sigma_{m1}^2}{N\sigma_{m1}^2+\sigma_n^2} \tag{37}$$

$$q=\frac{\sigma_{m2}^2}{N\sigma_{m2}^2+\sigma_n^2} \tag{38}$$

$$a=\sum_{n=1}^{N}e^{jn\pi[\sin\theta_{m1}-\sin(\theta_{m1}+\frac{\Delta\theta}{2})]} \tag{39}$$

$$b=\sum_{n=1}^{N}e^{jn\pi[\sin\theta_{m1}-\sin(\theta_{m1}+\Delta\theta)]} \tag{40}$$

Although, the analytical solution of above inequality cannot be calculated, one can get any resolution value under certain conditions through computer programming.

V. Simulation Results

In this section, we devise several simulation scenarios to verify the validity of the proposed algorithm. The error estimation and convergence behavior of the proposed algorithm under different step-sizes and SNRs are deeply studied. We also compare the proposed algorithm with the MUSIC algorithm.

A. Impact of SNR on the convergence and DOA estimation of the proposed algorithm

In this simulation, we assume a ULA with eight half-wavelength spaced sensors. One narrowband source with fixed step size μ=0.00002 is assumed to impinge the array from $\theta_1=30°$. The effect of the SNR on the DOA estimation and convergence is analyzed in this scenario. Fig. 3 shows the MSE along the iterations for three different SNRs, estimated from the ensemble-average of 500 independent runs.

It is observed from the MSE learning curve in Fig. 3 that as the SNR increases, the convergence become faster. The convergence time is about 25 iterations when SNR=30 dB, while it take about 150 iterations to converge when SNR=20 dB and for SNR=10 dB, it converges in about 500 iterations. So, convergence rate is directly proportional to SNR.

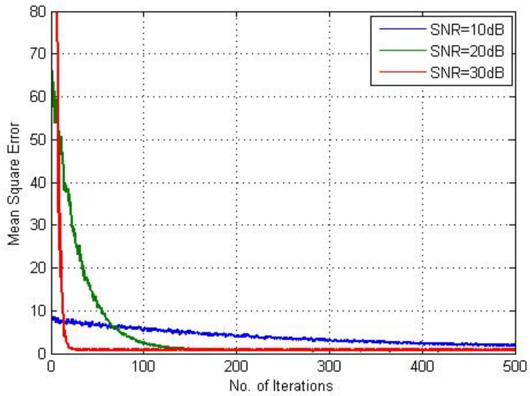

Fig. 3. The output Error curve under constant step.

Fig. 4 shows the spatial spectrum of the proposed algorithm reflects the relationship between $P(\theta)$ and SNR.

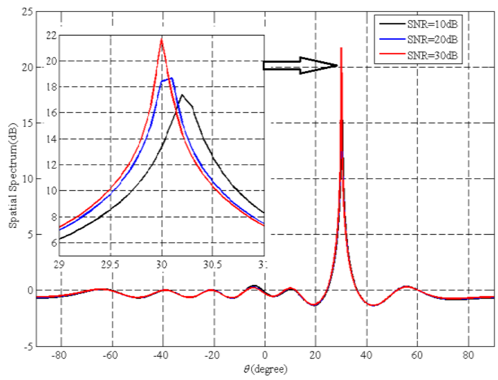

Fig. 4. The corresponding space spectrum under different SNRs.

Fig. 4 shows the spatial spectrum of the signal for $\theta\in[-90°,\ 90°]$ and the zoom-part for interval $\theta\in[29°,\ 31°]$. From the spatial spectrum of the Fig. 4, it is observed that as the SNR increases, the DOA estimation error decreases and the resolution is improved.

B. Impact of step-size on the convergence time and DOA estimation on the proposed algorithm

Assume the identical scenario as above, the signal impinges on the array from the direction $\theta_1=60°$, with fixed SNR=20 dB, and different iteration steps μ. The impact of step size on the DOA estimation is analyzed. Fig. 5 shows the MSE along the iterations for three different step-sizes, estimated from the ensemble-average of 500 independent runs.

Fig. 5 is the MSE learning curve that reveals the relationship between the convergence speed and step-size. For smallest step size, the convergence is the slowest. The convergence time is about 300 iterations for μ=0.01/1000. For large step size, μ= 0.01/100, the convergence is the fastest with only 25 iterations. Large step-sizes speed up the convergence of the algorithm, but also lower the precision of the steady-state solution of the algorithm. This effect can be seen in Fig. 6 given below. In-depth analysis of this behavior is briefly analyzed in the previous sections.

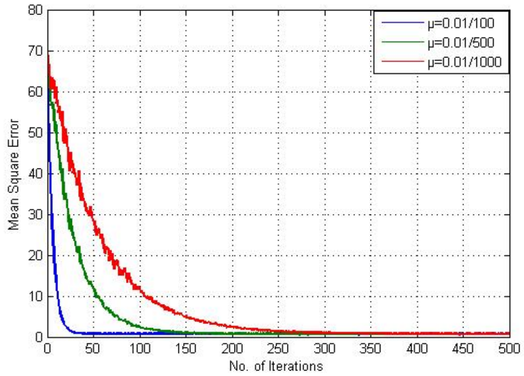

Fig. 5. The output Error curve under constant SNR.

Fig. 6 shows the spatial spectrum of the signal for $\theta \in [-90°, \ 90°]$ and the zoom-part for interval $\theta \in [58°, \ 62°]$. From the spatial spectrum of the Fig. 6, it can be observed that smaller the step size μ, DOA estimation error is smaller and higher will be the resolution.

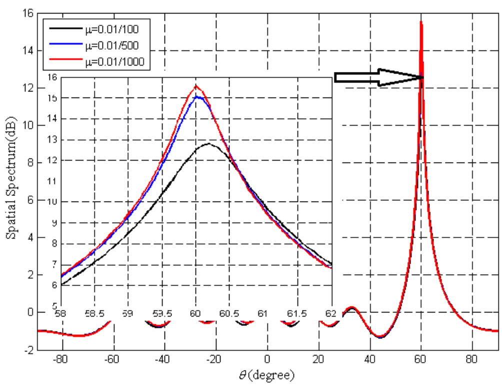

Fig. 6. The corresponding space spectrum under different steps.

C. Comparison with the MUSIC algorithm

In this simulation, we assume a ULA with eight half-wavelength spaced sensors. We evaluate the performance of the algorithms when two narrowband sources are assumed to impinge the array from 30° and 60°. The SNR is set to 10 dB for the target from 30°, and 20 dB for the one from 60°.

Fig. 7 shows the spatial spectrum of the proposed algorithm and the MUSIC algorithm. It can be seen from the figure that both the proposed and the MUSIC algorithms accurately locate the targets. The result shows that, for a large SNR signal of 60°, the peak is high and the resolution is more. It is also observed that the two algorithms achieve similar performance. The performance of the proposed algorithm approaches the MUSIC algorithm when SNR equals 10 dB (for 30° DOA case) in terms of resolution and accuracy. Moreover, when SNR equals 20 dB (for 60° DOA) , the narrow peak of the proposed algorithm slightly outperforms the MUSIC algorithm by yielding narrow peak as compared to MUSIC algorithm.

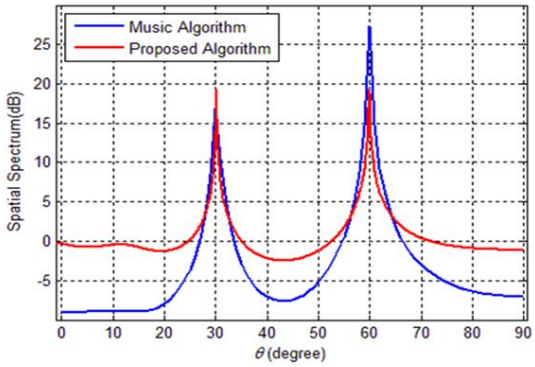

Fig. 7. Comparison of proposed algorithm with the MUSIC algorithm

To further illustrate the superiority of the proposed algorithm when the separation distance between sources is small, we do the following simulation. Consider the identical array condition as previously, the two narrowband sources with DOA 30° and 45° strike a ULA with eight half-wavelength spaced sensors. Fig. 8 shows the spatial spectrum for this scenario. It is observed that both algorithms estimate the DOA for two signals accurately even if the angle separation between signals is smaller.

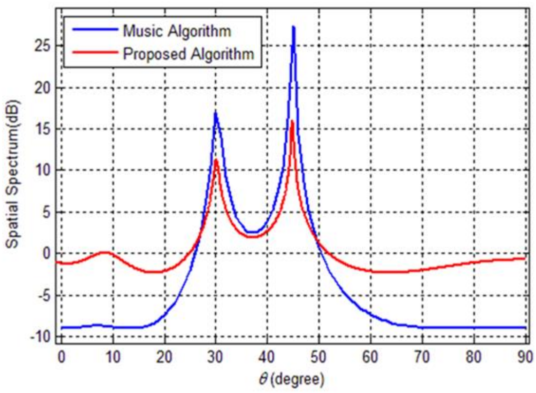

Fig. 8. Comparison of proposed algorithm with the MUSIC algorithm when the two sources lie close to each other

VI. CONCLUSION

A new algorithm for estimating direction-of-arrival (DOA) has been proposed in this paper. The new algorithm achieves DOA estimation utilizing the nulling antenna algorithm. Simulations show the simplicity and accuracy of the proposed methodology. Analysis of results shows that by a careful selection of the step-size, both the accuracy and resolution can be further improved. Compared with the MUSIC algorithm, the new algorithm eliminates the need of source number estimation and decomposition of covariance matrix, thus making the new algorithm less computational complex. Moreover, the proposed algorithm maintains high resolution in a very elegant and simple manner along with sustaining the distinctive feature of low computational complexity.

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