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Optimal Window Length and Performance Analysis of FEDS Based Adaptive Beam Forming Approach over Rayleigh Fading Channel

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Abstract: To the best of my knowledge, the concept of the Fast Euclidean Direction Search (FEDS) for the wireless communication systems has not been fully exploited and only a few researchers who are working on this topic. This paper deals with study and analysis overall FEDS approach performance and try to find its optimal window length (L) for adaptive beam forming applications. The channel used is a Rayleigh fading model with Jake's power spectral density, which is a popular choice for wireless communications systems. This channel model has Doppler frequency and the user's mobility parameters. The current investigation may be extended to include other adaptive algorithms such as Least Mean Square (LMS), Normalized LMS (NLMS), and Recursive Least Square (RLS) algorithms. Performance enhancement of FEDS approach can be obtained when the optimum window length (L) is a carefully selected and its value is related to or depends on the number of array elements (M) whether the channel is AWGN or Rayleigh fading models.

Keywords: Adaptive Beam forming, FEDS, RLS, LMS, NLMS, Rayleigh channel model.

1. INTRODUCTION

Adaptive Beam forming is an intelligent technique that consists of an array of multi-element antennas. These multi-element antennas try to direct main beams towards each user in the wireless communications system and achieve maximum reception in a specified direction by estimating the arrival of the signal from the desired direction while rejecting signals from other directions. The Euclidean Direction Search algorithm (EDS) is a least squares algorithm that was applied to different adaptive systems applications [1,2]. Both EDS and RLS algorithms have a fast and comparable convergence rate, and small miss-adjustment compared to the traditional Least Means Squares (LMS) and Normalized LMS (NLMS) algorithms [3,4]. However, EDS and RLS have a disadvantage which was suffering from high computational complexity. In order to overcome the disadvantage of EDS, a new algorithm was developed and was called Fast EDS (FEDS). This developed algorithm has a convergence rate slower than the EDS, but much faster than the LMS algorithm [5] and it was applied successfully for different adaptive filtering applications [6,7]. To the best of the author's knowledge, adaptive beam forming system based on the FEDS approach is very little available in the literature [1-10]. In our previously published papers [8-9] , the FEDS algorithm was applied in smart antennas for mobile communications using the AWGN channel and it concluded that the convergence rate of the FEDS is faster than LMS , and the same as the NLMS algorithms. Moreover, it was shown that the FEDS algorithm has better tracking and estimation capability of the input desired signal compared with LMS and NLMS algorithms, and comparable with the RLS algorithm [8-9].

The aim of this paper is to investigate the effectiveness of the described FEDS algorithm in the wireless communication systems and analyze its performance over a Rayleigh fading channel with Jake's power spectral density. This channel model has Doppler frequency and the user's mobility parameters. It also provides a complete comparison between the described FEDS algorithm and other aforementioned classical algorithms (LMS , NLMS ,and RLS). Afterward, an optimal window length (L) for FEDS was tried to find.

2. BACKGROUND ON LMS, NLMS , AND RLS ALGORITHMS

The adaptive beam forming algorithm system can be drawn as in Figure 1 [11]. This figure shows that the

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weight vector or array weights $\overline{w}(k)$ must be varied to minimize the error signal (ε(k)), where k is the time index.

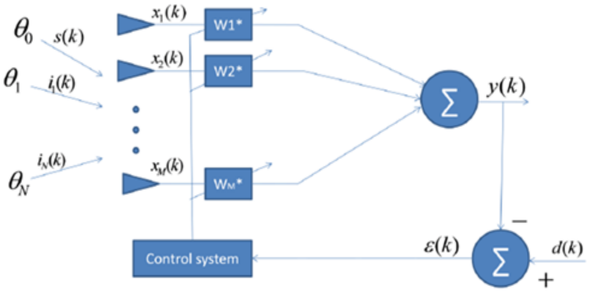

Figure 1. Adaptive beam forming system [11]

For the LMS algorithm, the array output can be written as:-

$$y(k) = \overline{w}(k)^H . \overline{x}(k \quad (1)$$

Where

$$\overline{x}(k) = \overline{a}_0 s(k) + [\overline{a}_1 \overline{a}_2 \; .... \overline{a}_N] . \begin{bmatrix} i_1(k) \\ i_2(k) \\ \vdots \\ i_N(k) \end{bmatrix} + \overline{n}(k)$$

$$= \overline{x}_s(k) + \overline{x}_i(k) + \overline{n}(k)$$

With

$\overline{w} = [w_1 w_2 \; .... w_M]^T$ is array weights vector, and

$\overline{x}(k) = [x_1 x_2 \; .... x_M]^T$ is input signalvector

$\overline{x}_s(k)$ is desired signal vector

$i_1(k), i_2(k), \dots \dots, i_N(k)$ are interfering signals.

$\overline{x}_i(k)$ Is interfering signal vector

$\overline{n}(k)$ is Gaussian noise with zero mean for each channel.

$\overline{a}_i$ is M-element array Steering vector.

$\varepsilon(k)$ is error signal such that:

$$\varepsilon(k) = d(k) - \overline{w}^H(k)\overline{x}(k) \quad (2)$$

For the LMS algorithm,the updating weight vector is [10]:

$$\overline{w}(k+1) = \overline{w}(k) + \mu \, \varepsilon(k)\overline{x}(k) \quad (3)$$

The stability of the LMS algorithm is guaranteed if the step size parameter (μ) has the following bound condition :

$$0 \le \mu \le \frac{1}{2\lambda_{max}} \quad (4)$$

Where λ_{max} is the maximum eigenvalue of the input correlation matrix estimation $\hat{R}_{xx}$, which can be instantaneous estimates as:-

$$\hat{R}_{xx}(k) \approx \overline{x}(k)\overline{x}^H(k) \quad (5)$$

The condition mentioned in Eq.(4) can be approximated as:-

$$0 \le \mu \le \frac{1}{2trac[\hat{R}_{xx}]} (6)$$

The updating weight vector of NLMS can be updated by [10]:-

$$\overline{w}(k+1) = \overline{w}(k) + \frac{\mu_0}{\|\overline{x}(k)\|^2} \varepsilon(k)\overline{x}(k) \quad (7)$$

Where μ_0 is a small positive constant. Recursive least squares (RLS) is an adaptive algorithm that is based on the least squares method which tries to minimize a weighted linear least squares cost function . Initialize the weight vector and the inverse correlation matrix $\hat{R}_{xx}^{-1}$. The constants forgetting factor λ and regularization δ parameters are set by the user. The forgetting factor is roughly a measure of the memory of the algorithm; its value should be less than unity. And the regularization parameter's value is determined by the signal- to- noise ratio (SNR) of the signals.[12]. Initialize the weight vector and the inverse correlation matrix $\hat{R}_{xx}^{-1}$.

$$\overline{w}^H(0) = \overline{0} \quad (8)$$

$$\hat{R}_{xx}^{-1}(0) = \delta^{-1}\overline{I} \quad (9)$$

The vector π is used to compute the gain vector $\overline{g}$ (also known as the search direction at iteration k) .For each instance of time k = 1, 2, 3 …,

$$\pi(k+1) = \hat{R}_{xx}^{-1}(k)\overline{x}(k) \quad (10)$$

$$\overline{g}(k) = \frac{\pi(k)}{\lambda + \overline{x}^H(k)\pi(k)} \quad (11)$$

Update the weights:

$$\overline{w}(k+1) = \overline{w}(k) + \varepsilon(k)\overline{g}(k) \quad (12)$$

Given an initial estimate of $\overline{w}(k)$ and the search direction $\overline{g}(k)$, the process of minimizing the next objective function is called line direction.

Then, the inverse correlation matrix is recalculated, and the training resumes with the new input values.

$$\hat{R}_{xx}^{-1}(k+1) = \lambda^{-1}\hat{R}_{xx}^{-1}(k) - \lambda^{-1}\overline{g}(k)\overline{x}^H(k)\hat{R}_{xx}^{-1}(k) \quad (13)$$

3. FEDS APPROACH FOR ADAPTIVE BEAMFORMING

FEDS approach is a simplified or partial RLS algorithm [6,7]. It combines the benefits of fast convergence of the RLS algorithm and low computational complexity of the LMS algorithm. FEDS approach updated the weight vector in a sequential way. FEDS approach used block exponential weighted least squares form instead of conventional exponentially one. The length of this block or window length is denoted by L, such that the weights will decrease exponentially with every block (L) of data. The error signal (Eq. (2)) can be re-written as:

$$\varepsilon(k) = d(k) - \sum_{i=1}^{M} w_i(k) x_i(k) \quad (14)$$

Assuming the samples k-L, k-L+1, k-L+2 …... k, where L>M, and L is a window (block) length (number of samples) as mentioned above. Equation (14) can be written in a vector form as

$$\bar{\varepsilon}(k) = \bar{d}(k) - \bar{X}(k)\bar{w}(k) \quad (15)$$

Where $\bar{X}(k) = [\bar{x}_1(k), \bar{x}_2(k) \dots . \bar{x}_M(k)]$ (16)

The column vector of $\bar{X}(k)$ are as follows:-

$$\bar{x}_j(k) = [x_j(k), x_j(k-1) \dots x_j(k-L+1)]^T \quad (17)$$

Also, the desired signal vector samples are:

$$\bar{d}(k) = [d(k), d(k-1), d(k-2) \dots d(k-L+1)]^T \quad (18)$$

Furthermore, we can define the error signal vector $\bar{\varepsilon}(k)$in the same way. The prior approximation error $\bar{\varepsilon}_0$ at time k is given by:

$$\bar{\varepsilon}_0(k) = \bar{d}(k) - \bar{X}(k-1)\bar{w}(k-1) \quad (19)$$

Only one weight in past updating weight vector has a new error signal as [6]:

$$\bar{\varepsilon}_1(k) = \bar{d}(k) - [\bar{X}(k)\bar{w}(k-1) + \bar{X}(k)\bar{w}^{update}_{j_0(k)}(k)\bar{F}_{j_0(k)} \quad (20)$$

The index of the weight to be updated in the zero'th iteration at time k is $j_0(k)$ and $\bar{F}_{j_0(k)}$ is M x 1 vector with 1 in position j and 0 in all other positions. Then, the updated weight $\bar{w}_{j_0(k)}(k)$ is given by:

$$\bar{w}_{j_0(k)}(k) = \bar{w}_{j_0(k)}(k-1) + \bar{w}^{update}_{j_0(k)}(k) \quad (21)$$

Where $\bar{w}^{update}_{j_0(k)}(k)$is given as:

$$\bar{w}^{update}_{j_0(k)}(k) = \frac{<\bar{\varepsilon}_0(k)\bar{x}_{j_0(k)}(k)>}{\left\|\bar{x}_{j_0(k)}(k)\right\|^2} \quad (22)$$

Where $<..>$ is the inner product of two vectors. Thus, the update array weight vector:

$$\bar{w}^o(k) = \bar{w}(k-1) + \bar{w}^{update}_{j_0(k)}(k)\bar{F}_{j_0(k)} \quad (23)$$

Then a new parameter called the step size μ_{FEDS} will be inserted to possess stability and convergence rate of the FEDS algorithm as follows:

$$\bar{w}^o(k) = \bar{w}(k-1) + \mu_{FEDS}\bar{w}^{update}_{j_0(k)}(k)\bar{F}_{j_0(k)} \quad (24)$$

Then substituting Eq.(24) into Eq.(20) , we get:-

$$\bar{\varepsilon}_1(k) = \bar{d}(k) - \bar{X}(k)\bar{w}^o(k) \quad (25)$$

Filter coefficient update equations updating only one element of the filter vector at a time. At each time instant, k , we can perform one or more such updates. The number of such single coefficient updates performed at each time instant is denoted by P . only one element of $\bar{w}^o$ is to be updated at a time, where Pis the number of updates to perform at each sample time [10] . The FEDS algorithm was formulated [1] as a simplified conjugate gradient adaptive filter in which the search directions were restricted to the Euclidian directions. FEDS approach can find better estimation weights vector in the duration of each direction by starting with an initial estimate value of weight vector and then using linearly independent Euclidean direction set, such that FEDS approach performs one Euclidean direct search for every iteration. FEDS approach has better performance than traditional LMS and NLMS algorithms, but comparable to the RLS, due to the FEDS approach is regarded as partial or alternative of full RLS [6,7].

4. THE JAKES FADING MODEL

Jacked model is fading radio channels that can be simulated by approximate the Rayleigh fading process by a sum of a set of N_0-complex sinusoids. This model was proposed by William Jakes of Bell laboratories [13] .

This model can be simulated using MATLAB built- in function called jakes_ralfunc(fm; fc; M; N_0; index), where fm is the maximum Doppler frequency of the channel; fs is the sampling rate of the fading process ; M is the number of samples of the fading process ; N_0 is the number of complex-sinusoids in the Jakes Model. The maximum Doppler frequency fm is related to the maximum vehicle speed vm by fm = vmfc/c, where, fc is the RF carrier frequency and c is the speed of light [13]. Figure 2 shows the envelope that results of simulating Jakes fading model with N_0 =10, v = 140 kmph, the central carrier frequency f_c = 900 MHz, the symbol frequency f_s =500 kbps, and M = 1000000 .

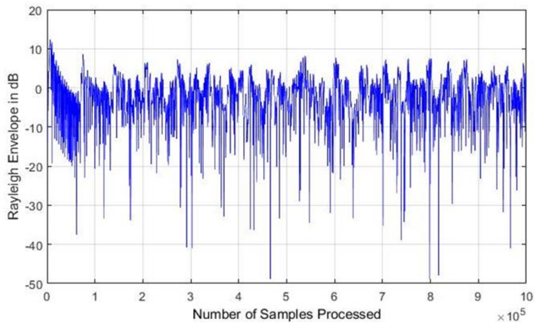

Figure2.Simulation of Jakes fading model with v = 140 km/h

5. Simulation Results

This section aims to develop a suitable simulation model for assessing the performance of the FEDS algorithm which employs an array antenna as shown in Figure 1 . The following condition parameters are used in this simulation:-

- A linear array consisting of M= 8 isotropic elements with d=0.5λ element spacing**.**
- All signals used for both the desired and interfering signals undergo independent Rayleigh fading.
- Desired AOA of $\theta_0 = 0^0$ and two interfering signals, i_1 and i_2 with two AOA's, $\theta_1 = 30^0$, $\theta_2 = -30^0$
- Input signal $S(k)=\sin(2\pi f t(k))$ with f= 1/T=900 MHZ and the desired signal d(k)=S(k).
- Zero mean Gaussian noise with variance $\sigma_n^2 = 0.001$is added to the input signal for each element in the array.
- The Signal to Noise Ratio (SNR) and Signal to Interference Ratio (SIR) are set at 30 dB and 10 dB respectively.
- The step size of LMS is set according to (4) and (6).
- Initial step size parameter μ_0 =1 , λ =0.9 for RLS.
- Rayleigh fading channel with Jake's power spectral density corresponding to the mobility of 140 km/h at 900 MHz and a Doppler frequency of 117 Hz, as shown in Figure 2 is used.
- All weight vectors are initially set to zero.

A. The Effect of setting the number of iterations (k)

Figure 3 and 4 show the performance of the FEDS algorithm in terms of an array output signal and squared error respectively when using a different number of iterations (i.e. k =100,150,200, and 300). Given that the desired input signal as mentioned above was $S(k)=\sin(2\pi f t(k))$. It is clear that better output array signal estimation was achieved for k=200 iterations and it degrades when using a small number of iterations which is the case that most properly faced in the mobile communications due to the requirements of fast-moving targets. The array output departs from the desired signal when the number of samples becomes larger than or smaller than 200 iterations because of several reasons. The most important reasons are that a large number of samples (k=300) causes an increase of the misadjustment at steady state (called excess error), and the small number of samples (k= 150 or 100 samples) is not enough to estimate the desired signal. These reasons affected the number of the Euclidean directions needed by the FEDS approach to decrease of the cost function.

Figure 4 shows a squared error signal for different sets of iterations for the FEDS approach. It is obvious that when the number of iterations was set to 200, the FEDS approach gives better performance in terms of convergence rate (20 iterations) .Therefore, the number of iterations (k) used in all cases was set to k=200.

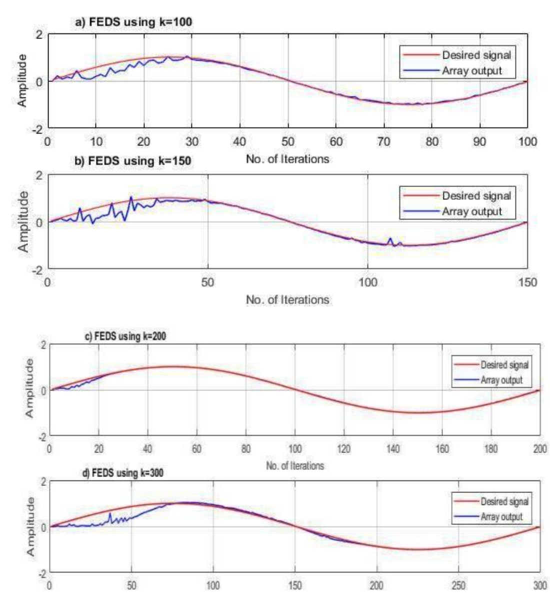

Figure 3. Array output and desired signals for different sets of iterations (k); a) k=100 , b) k=150 , c) k=200 , and d) k=300 iterations.

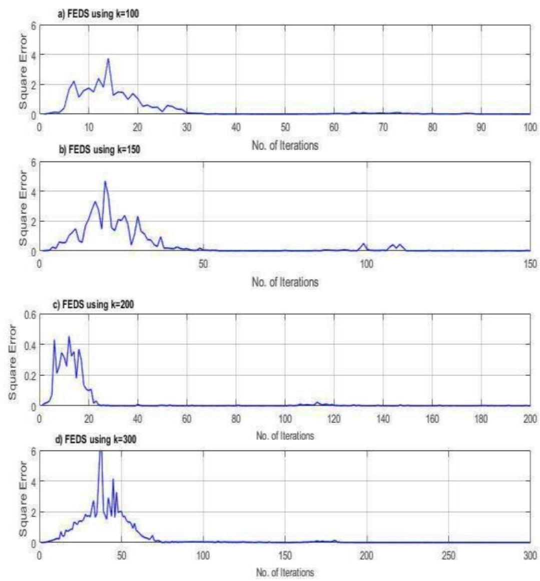

Figure 4. Error squared for the FEDS algorithm for different sets of iterations

B. *Overall Performance of FEDS*

Figure 5 shows the squared error for all algorithms. As shown in this figure, the RLS algorithm starts to converge from the initial iteration. Also, the results show that the FEDS algorithm has better or performance enhancement compared to both LMS and NLMS in terms of fast convergence and a small level of misadjustment. Each algorithm has the following convergence rate; 70, 30 and 20 iterations for LMS, NLMS, and the FEDS algorithm respectively.Figure 6 shows the magnitude estimation of the weight vector for all algorithms. As shown in these figures, the performance of the FEDS is better than the LMS and NLMS algorithms and comparable with the RLS algorithm.

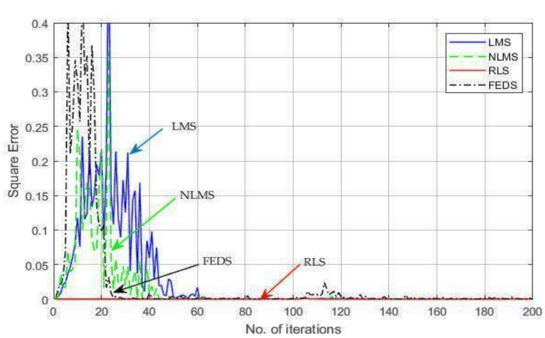

Figure 5. Error squared for all algorithms

C. *The Effect of window lengths L on FEDS performance*

In this section, the FEDS algorithm is evaluated for different window lengths (L) and compared with other traditional adaptive algorithms (LMS, NLMS , and RLS)

The Desired Angle of Arrival (AOA) of 00 and two interfering signals with AOAs, 300 and -300 respectively. The Mean Square Deviation (MSD) of the weights and the Mean Square Error (MSE) are computed for 100 average ensembles run for every 200 iterations. The Rayleigh Envelope that results for user mobility of v = 100 km/h is shown in Figure 7.

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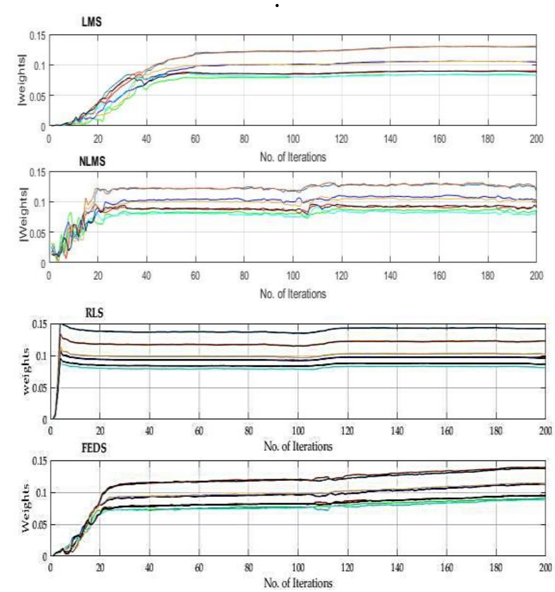

Figure 6. Magnitude estimation of the weight vector for all algorithms

Figure 8 shows the radiation pattern for the different window length (L) of the FEDS algorithm. As shown in this figure, the FEDS10 (i.e. FEDS used L=10) has better interference suppression capability at interference angles 30^0 and -30^0 compared with the others.

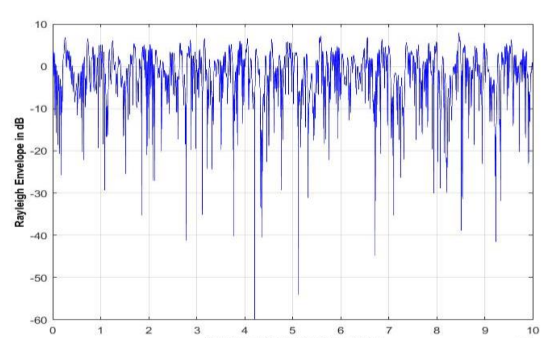

Figure 7. Simulation of Jakes fading model with v = 100 km/h

The radiation pattern for FEDSS06 and FEDS20(i.e. FEDS used L=6, and L=20 respectively) has deviated and lost symmetry property compared to other algorithms which kept having symmetry property, like FEDS8 , FEDS10, FEDS12, LMS , NLMS , and RLS . This deviation caused because the window length (L=6 or L=20) affected the number of the Euclidean directions needed by a FEDS approach to decrease the cost function. Moreover, the interference suppression capability of both FEDS06 and FEDS20 are in a minimum state. Table 1 shown later, illustrates the suppression capability of interference for all algorithms.

Figure 9 presents the Mean Square Deviation (MSD) plot for this case and as shown the FEDS10 has better minimum MSD performance compared with the other block size of the FEDS algorithms. Figure 10 shows the Mean Square Error (MSE) learning curve for different block sizes of FEDS algorithm which shows that the FEDS10 has a minimum MSE performance compared with others. We can conclude that the optimum window length (L) for an array consists of 8 elements and using a Rayleigh fading channel equal to ten which is a similar value obtained in our previous paper [9] when we used AWGN channel.

Figure 11 shows the radiation pattern for FEDS10, LMS, NLMS, and RLS algorithms. As shown in this figure the interference suppression capability of FEDS10 is comparable with the RLS algorithm and both are better compared with NLMS and LMS algorithms respectively. Table 1 shows the amount of interference suppression performance for all algorithms.

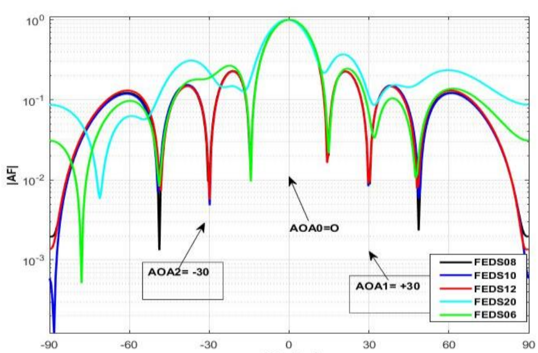

Figure 8 .Radiation patterns for window length (L) of the FEDS algorithm

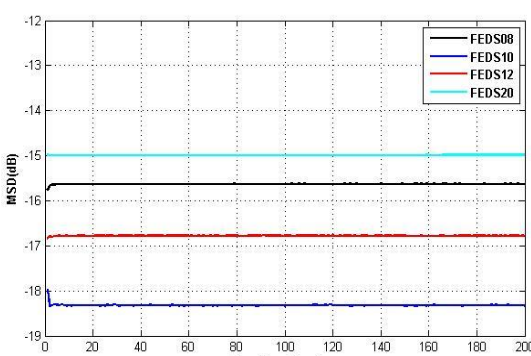

Figure 9. MSD plot for different window length (L) of FEDS algorithm

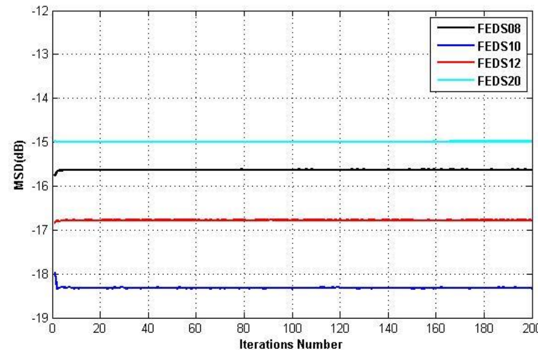

Figure 10. MSE learning curve for window length (L) of FEDS algorithm

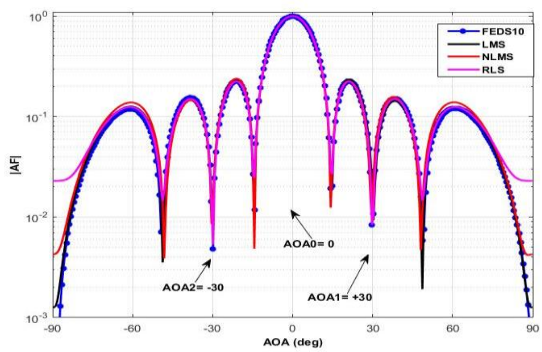

Figure 11.Radiation patterns for all algorithms

TABLE. 1 INTERFERENCE SUPPRESSION CAPABILITY FOR ALL ALGORITHMS

Algorithm	30^0	-30^0
FEDS06	Deviated	Deviated
FEDS08	-20 dB	-20 dB
FEDS10	-22 dB	-25 dB
FEDS12	-21 dB	-24 dB
FEDS20	Deviated	Deviated
RLS	-21.5 dB	-24.5 dB
NLMS	-21 dB	-21 dB
LMS	-20.5 dB	- 19.5 dB

Figures 12 and 13 shows the MSD and MSE learning curve plots for this case, and as shown that the RLS algorithm outperforms performance in terms of minimum MSD and MSE in a steady-state than others. In addition, both RLS and FEDS10 have a faster convergence rate compared with both LMS and NLMS algorithms respectively. From the above results, we can observe that the best window length parameter (L) is ten and the FEDS's performance starts to decrease when the window length parameter (L) has another value.

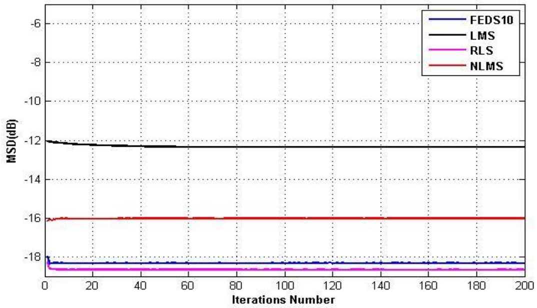

Figure 12 MSD plot for all algorithms

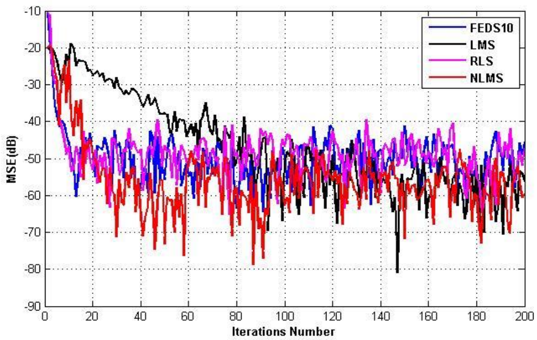

Figure 13 MSE learning curves plot for all algorithms

6. CONCLUSION

This paper study and reported the overall performance analyses of an adaptive beam forming a FEDS approach and tried to find its optimal window length (L) over the Rayleigh fading model. From the obtained results, we observed that the FEDS approach has better performance than classical algorithms, except the RLS algorithm, in terms of convergence rate, weight estimations, and fluctuation rate. Both RLS and FEDS approach generates null towards the undesired signals and both have the main beam pointed towards the desired location. Moreover, the side lobe array levels of the FEDS approach are lower than the RLS algorithm. The best value for the window length (L) of the FEDS approach should be slightly higher (L= M+2) than the number of array elements (M) in order to achieve good performance than classical algorithms, in terms of MSE, MSD, and undesired signal cancellation but comparable with the RLS algorithm. Optimum window length (L) is related to or depends on the number of array elements (M), such that L=M+2, whether the channel is AWGN or Rayleigh fading model. Moreover, the symmetry property of the radiation pattern for a FEDS approach is very sensitive to the window length (L).

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