A New Switched-beam Setup for Adaptive Antenna Array Beamforming

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Abstract

In this paper, a new spatio-temporal based approach is proposed which improves the speed and performance of temporal-based algorithms, conventional Least Mean Square (LMS), Normalized LMS (NLMS) and Variable Step-size LMS (VSLMS), by using the switched beam technique. In the proposed algorithm, first, DOA of the signal source is estimated by MUltiple SIgnal Classification (MUSIC) algorithm. In the second step, depending on the desired user's location, the closest beam of the switched beam system is selected and its predetermined weights are chosen as the initial values for the weight vector. Finally, LMS/NLMS/VSLMS algorithm is applied to initial weights and final weights are calculated. Simulation results show improved convergence and tracking speed and also a higher efficiency in data transmission through increasing the Signal to Interference plus Noise Ratio (SINR) as well as decreasing the Bit Error Rate (BER) and Mean Square Error (MSE), in a joint state. Moreover, Error Vector Magnitude (EVM) as a measure for distortion introduced by the proposed adaptive scheme on the received signal is evaluated for all LMS-based proposed algorithms which are approximately the same as that for conventional ones. In order to investigate the tracking capability of the proposed method, the system is assumed to be time varying and the desired signal location is considered once in the centre of the initial beam and once in the edge of the fixed beam. As depicted in simulation results, the proposed DOA-based methods offer beamforming with higher performance in both cases of the initial beam, centre as the best case and edge as the worst case, with respect to conventional ones. The MSE diagrams for this time varying system show an ideal response for DOA-based methods in the best case. Also, in the worst case, initial height of MSE is reduced and consequently the required iteration to converge is less than the conventional LMS/NLMS/VSLMS.

Keywords: Beamforming; Switched Beam; LMS; NLMS; DOA; MUSIC.

1. Introduction

Rapid growth of requests for wireless and mobile communication and increasing operators' demands has stimulated considerable studies for development of advanced techniques and technologies. The main goal is to manage the limited radio resources such as frequency spectrum and power and also attaining fully integrated, low cost, reliable, high quality and high speed wireless communications. Smart antennas or adaptive array antennas are effective solutions for these growing demands. They can make significant performance improvement for wireless systems, with respect to other methods such as low noise amplifiers, wideband techniques and sectorization. Smart antennas utilize adaptive beamforming techniques to provide optimum performance for the system. Higher capacity and data rate, lower power consumption, extended coverage range, reduction in noise and fading effects and suppression of interferers are advantages of antenna beamforming. Various methods exist for adaptive beamforming which can be implemented using high speed digital signal processing units [1]-[6].

The least Mean Square (LMS) algorithm is a popular algorithm for adaptive beamforming and other filtering applications such as interference cancellation, echo cancellation, noise cancellation, channel estimation and channel equalization. The LMS algorithm is a training-based method that employs a temporal training reference signal and recursively updates the weight vector to minimize Mean Square Error (MSE) between a reference signal and the array output. The advantages of LMS are simplicity, high stability, robustness and low computational cost which make LMS a widely-used algorithm. However, LMS suffers from low convergence and tracking speed. Therefore, a vast number of works in the literature are accomplished to enhance the performance of LMS as well as Normalized LMS (NLMS) which is a common version of LMS, and various types of LMS are proposed that attempt to boost the speed and efficiency of LMS/NLMS [7]-[10]. Different Variable Step-size LMS (VSLMS) algorithms are presented that attempt to reduce the convergence speed of the LMS [11], [12].

The combination of the LMS and other beamforming algorithms such as Sample Matrix Inversion (SMI) is also examined and has shown remarkable improvements in the

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convergence rate and interference suppression [13]. Also, a combination of Discrete Fourier Transform (DFT) and LMS algorithm is investigated for array antenna beamforming in [14]. This algorithm has improved the performance of both time-updating algorithm and spatial estimating. In [15] a new algorithm, called LLMS, is presented which combines the use of two successive LMS sections. Simulation results have shown better convergence performance of LLMS relative to the conventional LMS as well as Constrained Stability LMS (CSLMS), and Modified Robust Variable Step Size LMS (MRVSS) algorithms. The combination of Recursive Least Square (RLS) and LMS algorithms known as RLMS is also examined and RLMS algorithm has shown better performance than other earlier algorithms such as LMS, RLS, MRVSS and CSLMS [16]. A new adaptive beamforming algorithm called Turbo-LMS is presented in [17]. The proposed Turbo-LMS algorithm has given rapid convergence with respect to the LMS. All of the above mentioned algorithms are based on temporal information and they do not use the spatial information.

DOA estimation methods are effective techniques used for detection and tracking of the signal source location. These algorithms play a key role in blind beamforming techniques. Training-based algorithms, such as LMS/NLMS, generally do not need DOA estimation. However, DOA of the desired signals can be exploited to enhance LMS/NLMS beamforming performance and some investigations are accomplished in this regard.

In [18], a detection guided NLMS algorithm is proposed which incorporates DOA detection that leads to a reduction in the number of NLMS adapted parameters. This scheme significantly improved convergence and tracking speed, as well as the performance of nulling multi-user interference signals. In another research, DOA information which is generated through the Minimum Variance Distortionless Response (MVDR) method is used to build the constrained matrix needed for different constrained beamforming techniques. These algorithms have shown a good performance in terms of stability, convergence and accuracy [19]. Some other investigations have used the LMS and Multiple SIgnal Classification (MUSIC) algorithms simultaneously to cover desired DOAs and to null unwanted signals using both algorithms [4], [20]. In [21], [22] new LMS-based/CM-based adaptive weighting algorithm is proposed which relies on the idea of predicting the next location of source, and determining the array weights before arriving to the new location. For the next time associated to the new sampling point, evaluated weights will be used. Simulation results show lower on-line required processing with respect to conventional LMS. It can also predict the next location of the target in mobile applications.

Above mentioned proposed algorithms may not be extended easily for other weighting algorithms and special array geometry is needed. Also, it is desired to extend the proposed algorithm to multiuser detection applications. Therefore, the aim of this paper is to present a new approach which exploits the DOA information in training-based algorithms that consider temporal sequence as reference, especially, LMS and NLMS algorithms. Proposed method employs the switched beam technique to enhance the LMS and NLMS speed. This new combination can be applied for different array geometries and all types of training based weighting algorithms. Also, it can be used for multibeam scenarios.

Simulation results show a better performance as well as lower convergence time for the proposed algorithm in comparison with the standard LMS, NLMS and VSLMS algorithms. Finally, the proposed DOA-based temporal-reference beamforming algorithm offers increased convergence and tracking speed, in a joint state.

The rest of this paper is organized as follows. In Section 2, an overview of switched beam technique, adaptive arrays and adaptive beamforming approaches is presented. LMS, NLMS and VSLMS algorithms are described in Section 3. Also, popular DOA estimation algorithm, MUSIC, is described, briefly. Section 4 states the proposed beamforming technique and shows the different steps of the new algorithm. In Section 5, simulation results are given and new DOA-based LMS, NLMS and VSLMS algorithms are compared with conventional LMS, NLMS and VSLMS ones, respectively. Finally, conclusion remarks are given in section 6.

2. Smart Antenna Systems and Signal Model

Smart antenna systems are generally classified into two main categories: switched beam antennas and adaptive arrays.

In switched beam systems, multiple fixed beams are defined in several predetermined directions. In fact, the switched beam technique is an extension of the cellular sectorization scheme in which each 120° macro-sector is divided into several smaller micro-sectors. Each predetermined fixed beam belongs to one micro-sector. When a mobile user moves through the cell, the system selects an appropriate fixed beam which has the strongest received signal power. The system monitors the signal strength and switches between predetermined fixed beams if required. This scheme approaches a high performance in terms of array gain and coverage range of the base station of terrestrial wireless systems and also multi-beam satellites. However, since beams are fixed and each of them has the maximum gain in the centre of the beam, the system gain decreases in the edge of the predetermined beams. Therefore, the signal strength and quality of service degrade if the user approaches the edges of the main beam or if an interferer approaches the centre of the beam. Also, the switched beam systems cannot distinguish between desired and undesired signals such as interferers. Different hardware and software designs are available for implementation of switched beam systems [1], [3].

Adaptive array antenna systems continually monitor RF environment and adjust the antenna pattern dynamically to optimize the system performance as locations of users and interferers change. Adaptive array systems consist of an antenna array and a signal processing unit. This unit includes complex weights, a unit that combines the weighted received signals and a signal processor which computes optimum weights via adaptive beamforming algorithms. Beamforming algorithms optimize the antenna system efficiency with respect to the signal environment by focusing energy in the desired user's direction and cancelling interferer signals by creating appropriate nulls in the radiation pattern. Adaptive arrays have more capabilities than switched-beam systems and they provide more degrees of freedom [1]-[5].

Adaptive beamforming techniques may be either training-based or blind. Training-based or non-blind approaches use a reference signal to adapt weights. The reference signal is known in both the transmitter and receiver and is used for updating the weight vector at the receiver. LMS, NLMS, SMI and RLS are examples of training-based beamforming algorithms. Blind algorithms don't use the reference signal and are usually based on the known properties of the desired signal. Algorithms such as Constant Modulus (CM), Decision Directed (DD), Least Squares (LS) and Conjugate Gradient (CG) are categorized as blind algorithms [1], [5]. In this research, two well-known training-based algorithms, LMS and NLMS, are utilized for weight adaptation.

In the following, we assume that the array is composed of N sensors configured in a Uniform Linear Array (ULA) and M narrowband signals are received at the array. Received signals can be expressed as a linear combination of incident signals and zero mean Gaussian noise with variance σ_n^2. The incident signals are assumed to be direct Line Of Sight (LOS) and uncorrelated with the noise. The input signal vector can be written as follows:

$$x(t) = \sum_{m=1}^{M} a(\theta_m)\, s_m(t) + n(t) = A.S(t) + n(t) \tag{1}$$

$s_m(t)$ is a $M \times 1$ vector concerning to the m-th source located at direction θ_m from the array boresight. $a(\theta_m)$ is a $N \times 1$ steering vector or response vector of the array for direction θ_m, and is written as:

$$a(\theta_m) = \left[1,\ e^{-jk.d\sin\theta_m}, \dots, e^{-j(N-1)k.d\sin\theta_m}\right]^T \tag{2}$$

where d is the inter-element spacing value and $k = 2\pi/\lambda$ is the wavenumber.

Furthermore, A is a $N \times M$ matrix of steering vectors, which is named manifold matrix and expressed as:

$$A = [a(\theta_1)a(\theta_2)\ \ \dots\ a(\theta_M)] \tag{3}$$

The array output signal is given by:

$$y(n) = w^H x(n) \tag{4}$$

where w is the N dimensional weight vector, H denotes the Hermitian transpose, and x is the received signal vector as defined in (1).

3. Beamforming Using LMS, NLMS and VSLMS Algorithms

The LMS algorithm is a popular adaptation technique based on the steepest descent method. This algorithm updates the weights recursively by estimating gradient of the error surface and changing the weights in the direction opposite to the gradient to minimise the MSE [2]. The error signal is computed by the following expression:

$$e(n) = d(n) - y(n) \tag{5}$$

The final recursive equation for updating the weight vector is:

$$w(n+1) = w(n) + \mu x(n) e^*(n) \tag{6}$$

where $e(n)$ is the error signal, i.e., the difference between desired signal $d(n)$ and output $y(n)$, μ is the step size parameter which controls the convergence speed of the algorithm, and $x(n)$ is the received array. The small step size causes a slow convergence but high stability around the optimum value. On the other hand, large step size results in a rapid convergence and a lower stability. Hence, step size is a major parameter that makes a trade-off between the convergence speed and the stability. The convergence rate of the LMS also depends on the eigen-value spread of the input correlation matrix. Variable step size algorithms are used to increase the convergence rate [10],[11].

In (6), the correction term $\mu x(n)\, e^*(n)$ is applied to the weight vector during LMS algorithm, is proportional to the input vector $x(n)$. Therefore, a gradient noise amplification problem occurs in the standard LMS algorithm. This problem can be solved by normalized LMS, in which a data dependent step size is used for adaption. NLMS normalizes the weight vector correction term with respect to the squared Euclidean norm of the input vector $x(n)$ at time instant n. So the updating equation in NLMS can be written as follows:

$$w(n+1) = w(n) + \frac{\mu}{\|x(n)\|^2} x(n) e^*(n) \tag{7}$$

The NLMS algorithm shows a better performance than the LMS algorithm in terms of convergence and stability [2]. To avoid the convergence problem due to division by a small number, a positive constant ε may be added to the Euclidean norm of the input vector in (7), so the weight vector is computed through:

$$w(n+1) = w(n) + \frac{\mu}{\varepsilon + \|x(n)\|^2} x(n) e^*(n) \tag{8}$$

This algorithm is known as ε-NLMS and results in a more reliable implementation [7]. Since LMS and NLMS algorithms are temporal-based, their slow convergence may cause tracking problems in cellular mobile systems. The main mechanism used to control the convergence rate of LMS algorithm is changing the step-size of algorithm. Variable Step-size LMS (VSLMS) algorithm can enhance the performance of beamforming including convergence rate and steady state performance. Different types of VSLMS algorithm have been proposed in the literature [7], [8]. In VSLMS algorithm usually the step-size μ is limited between μ_{min} and μ_{max}. μ is calculated during each iteration using the gradient function of error in the previous iteration. In this paper, the VSLMS algorithm introduced by Kwong and Johnston is used for simulation [23]. The step-size is computed through equation (9).

$$\mu(n) = \alpha\mu(n-1) + \gamma e^2(n) \tag{9}$$

where $0 < \alpha < 1$ and $\gamma > 0$ and then the comparison of $\mu(n)$ is done as equation (10).

$$\mu(n) = \begin{cases} \mu_{max} & \text{if } \mu(n) > \mu_{max} \\ \mu_{min} & \text{if } \mu(n) < \mu_{min} \\ \mu(n) & \text{otherwise} \end{cases} \tag{10}$$

In the following section, a new approach is proposed which uses spatial DOA information beside adaptive weighting algorithms to achieve a better convergence speed in LMS, NLMS and VSLMS algorithms. Other LMS type algorithms also will be improved using this approach.

4. Music Algorithm

There are different methods to estimate the DOA that are divided into three basic categories, classical, subspace-based, and maximum likelihood (ML)-based. These techniques differ in modelling approach, computational complexity, resolution threshold and accuracy. Spectral-based methods, first and second categories, which rely on calculating the spatial spectrum of the received signal and finding the DOAs as the location of peaks in the spectrum, are easy to apply and need less computation than parametric or ML-based methods that directly estimate the DOAs without first calculating the spectrum [24,25].

Among them, MUSIC is a subspace-based DOA estimation algorithm referred to super-resolution technique which offers a good tradeoff between resolution and computational complexity. It should be noted that MVDR is not able to introduce high resolution peaks, Root-MUSIC is an appropriate algorithm only for ULA and the Estimation of Signal Parameters via Rotational Invariance Technique (ESPRIT) algorithm needs special array geometry, but the MUSIC algorithm offers high resolution peaks which can be used for different array geometries [25].

Eigenvectors of the covariance matrix belong to either two orthogonal signal or noise subspaces. If M signals arrive on the array, M Eigenvectors associated with the M largest eigenvalues of the covariance matrix span the signal subspace and the $N-M$ Eigenvectors corresponding to the $N-M$ smallest eigenvalues of the covariance matrix span the noise subspace. The M steering vectors that form the manifold matrix $A(\theta)$ are orthogonal to the noise subspace and so the steering vectors lie in the signal subspace.

The MUSIC algorithm estimates the noise subspace using Eigen-decomposition of the sample covariance matrix and then estimations of DOAs are taken as those θ that give the smallest value of $A^H(\theta)V_n$, where V_n denotes the matrix of Eigen-vectors corresponding to the noise subspace. These values of θ result in a steering vector farthest away from the noise subspace and orthogonal to the noise subspace as much as possible [26], [27]. This is done by finding M peaks in the MUSIC spectrum defined by:

$$P_{MUSIC}(\theta) = \frac{1}{A^H(\theta)V_n{V_n}^H A(\theta)} \tag{11}$$

Several parameters such as the number of samples (snapshots), the number of elements and also SNR affect the resolution threshold of the DOA estimation algorithms.

5. Description of the Proposed Method

The LMS algorithm and its variants are temporal training-based algorithms and they don't need DOA estimation of the signal sources for weight updating computations. To utilize DOA information in the LMS algorithm, the effect of signal source location is imposed on the initial value of the weight vector. This leads to a higher convergence rate. The new DOA-based algorithm utilizes switched beam scheme to choose an appropriate initial value for the weight vector. The angular space is divided into a plenty number of sections and a particular beam is determined for each section. An example of space division can be seen in Fig. 1. Each beam has a pre-determined weight vector that are previously, computed by the LMS, NLMS or VSLMS algorithms.

The proposed method in details is as follows.

5.1 The Preliminary Adjustment Phase

This step is carried out once before initiation of the beamforming and does not repeat in next beamforming processes. According to the required resolution and the array configuration, the angular space is divided into multiple sections of the same width and a particular beam is specified to each section as depicted in Fig. 1.

5.2 The Beamforming Phase

A set of weight vectors is calculated for the defined beams using the LMS/NLMS algorithm. The obtained weights will be saved in the memory of the system. In this phase, the initial adjustment of the system is accomplished and a set of predefined beams and their related weights are prepared for the DOA-based beamforming which is performed as the following steps.

Step 1: DOA of the signal source is estimated using a proper simple DOA estimation method such as MUSIC. In the case of multiple correlated signal sources, spatial smoothing methods same as Forward-Backward Spatial Smoothing (FBSS) can be used to help signal source detection [23].

Step 2: Depending on the desired user's location, the closest beam defined in the preliminary step is selected and its predetermined weights are chosen as the initial value for the weight vector.

Step 3: The LMS or NLMS algorithm is applied to initial weights and final weights will be calculated with a higher rate.

This step results in more accuracy in target tracking and nulling of the undesired signals. In the case of enough number of predetermined beams and absence of undesired signals, initial weights obtained in the second step can be satisfactory.

The preliminary adjustment and beamforming phases are depicted as flowcharts in Fig. 2 and Fig. 3, respectively.

6. Simulation Results

We consider a ULA with 8 elements and half wavelength inter-element spacing. The performance of the LMS, NLMS and VSLMS algorithms are investigated in different situations around one of the predetermined beams and compared with the conventional LMS, NLMS and VSLMS beamforming schemes. In this investigation, the NLMS is considered as ε-NLMS and VSLMS is considered as proposed by Kwong and Johnston [23]. In addition, for 8-elelment array, at least every 10 degrees of the space should be covered with a particular beam. So, the space is divided into several 10 degree sections with overlapped beams as demonstrated in Fig. 1.

The weight vector for each beam in a specific direction is computed through conventional LMS, NLMS and VSLMS considering single user application. The desired signal source direction is estimated using the MUSIC algorithm. It is expected that the proposed algorithm have the best and the worst performance at the centre and edges of the closest predetermined beam to the desired DOA, respectively.

To compare the conventional and the proposed spatial-temporal algorithms, the desired user's location is assumed to be at the centre of the beam placed at 25° of the best situation and at the edge of that beam at the worst case as shown in Fig. 4. Supposed that the Additive White Gaussian Noise (AWGN) is imposed to the transmitted signal and the

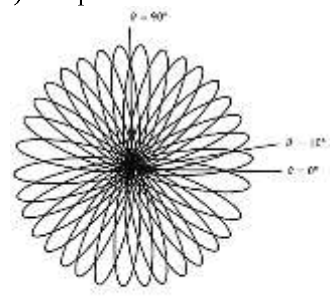

Fig. 1. Space divisions in switched beam scheme

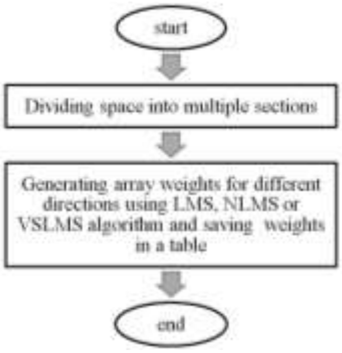

Fig. 2. The preliminary adjustment phase

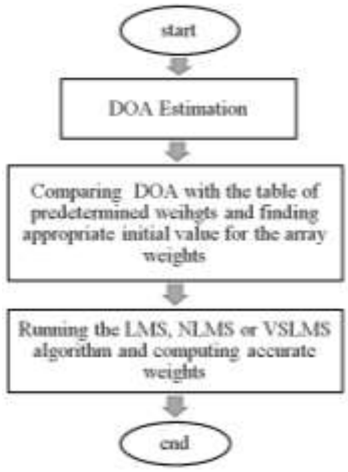

Fig. 3. The beamforming phase

Binary Phase Shift Keying (BPSK) modulation is used for data transmission. Two interference signals are also assumed to be received at $-15°$ and $70°$ with a 3 dB Signal to Interference Ratio (SIR). The convergence speed, Signal to Interference plus Noise Ratio (SINR), Bit Error Rate (BER) and MSE of the algorithms are computed via MATLAB and compared together.

Fig. 5 depicts the radiation pattern of the adaptive antenna array system when the desired signal is located at $25°$. The main lobe is placed accurately at the centre of the concerned beam when DOA is $25°$. Appropriate nulls are shaped at the direction of interferers via DOA-based techniques as well as conventional algorithms.

Fig. 6 shows the MSE changes during the training process, where DOA is placed at the centre of the considered beam ($\mathrm{DOA} = 25°$). In this case, DOA-based algorithms are converged at the beginning of the adaptation process.

For the considered beam at $25°$, signals arrive at $20°$ or $30°$ are located at the edges of the initial beam. In Fig. 6, the radiation pattern of the array is illustrated for LMS/NLMS/VSLMS and the DOA-based versions when DOA is placed at the edge of the considered beam ($\mathrm{DOA} = 30°$). Appropriate main beam and nulls are shaped in the direction of desired and interference signals, respectively. Some deviation may be seen at the location of the main lobe when DOA is $30°$. However, the array gain is equivalent or even greater at the desired signal DOA in DOA-based algorithms. By increasing the number of array elements or the number of predetermined fixed beams, the deviation will be decreased. Appropriate nulls are shaped at the direction of interferers via DOA-based techniques as well as the conventional algorithms.

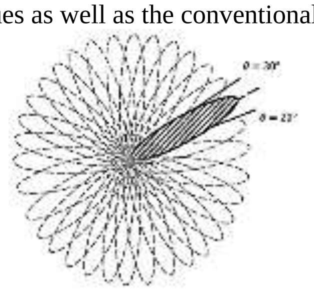

Fig. 4. Situation of the considered beam at $25°$

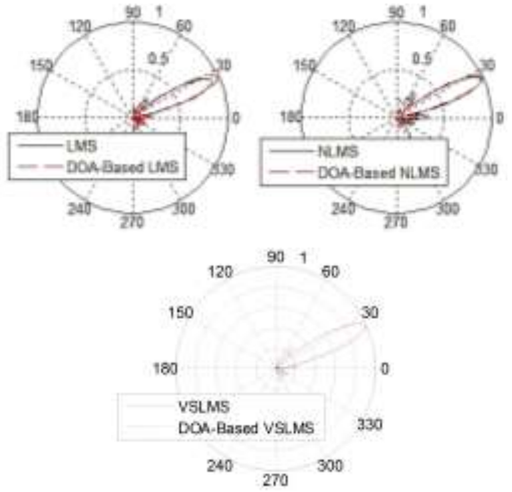

Fig. 5. Radiation Pattern of LMS/DOA-based LMS ,NLMS/DOA-based NLMS and VSLMS/DOA-based VSLMS when DOA = 25°

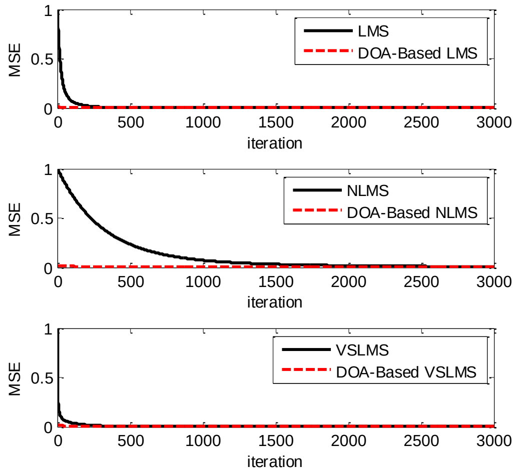

Fig. 6. MSE diagram during the training process when the desired DOA is in the centre of the initial beam

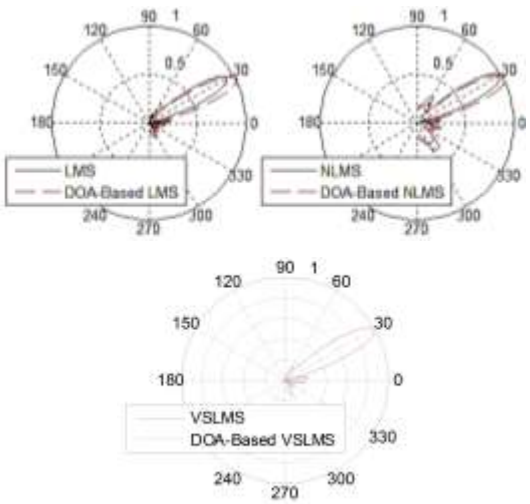

Fig. 7. Radiation Pattern of LMS/DOA-based LMS, NLMS/DOA-based NLMS and VSLMS/DOA-based VSLMS when DOA = 30°

Variations of the MSE during the training process for $\mathrm{DOA} = 30°$ is demonstrated in Fig. 8. The MSE diagrams also show a better convergence rate of the DOA-based algorithms than the conventional LMS/NLMS/VSLMS algorithms in this case. The lower MSE at the beginning of training process can be interpreted as better capability for adaptation with time-variant systems and moving target tracking. In other directions that are covered by this beam ($20° < \theta < 30°$), simulation trials give a better convergence speed than the edge of the initial beam.

In Fig. 9, 10, SINR versus the SNR for both the centre and edges of the initial fixed beam ($\mathrm{DOA} = 25°$) are shown. As the SNR rises, SINR increases. As expected, the level of SINR in the DOA-based methods is higher than the conventional algorithms.

The BER diagram in Fig. 11 presents a lower level for the DOA-based methods in the centre of the predetermined beam ($\mathrm{DOA} = 25°$). When $\mathrm{DOA} = 30°$, as seen in Fig. 12, the BER levels for both of the proposed and conventional algorithms are close together. The BER in other situations is lower than BER in the edges of the initial beam placed at 25°. Therefore, it can be concluded that the BER in the DOA-based methods is the same as or lower than the conventional methods.

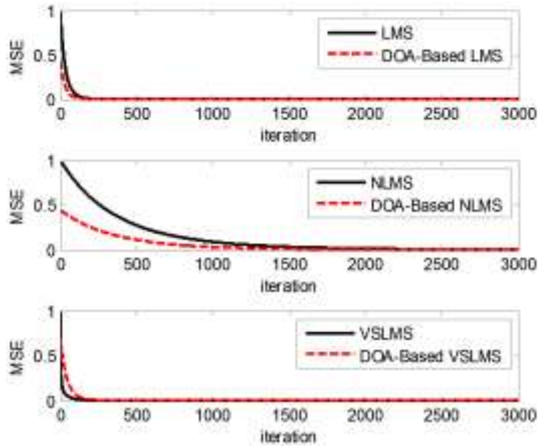

Fig. 8. MSE diagram during the training process when desired DOA is in the edge of the initial beam

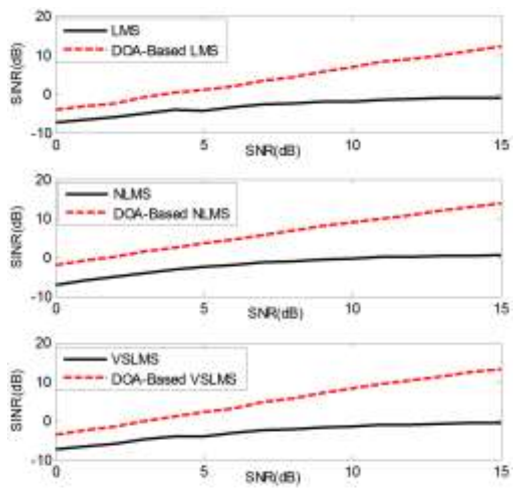

Fig. 9. SINR changes when the desired DOA is in the centre of the initial beam

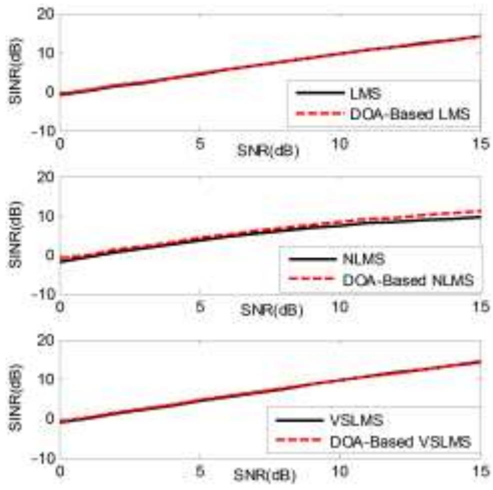

Fig. 10. SINR changes when the desired DOA is in the edge of the initial beam

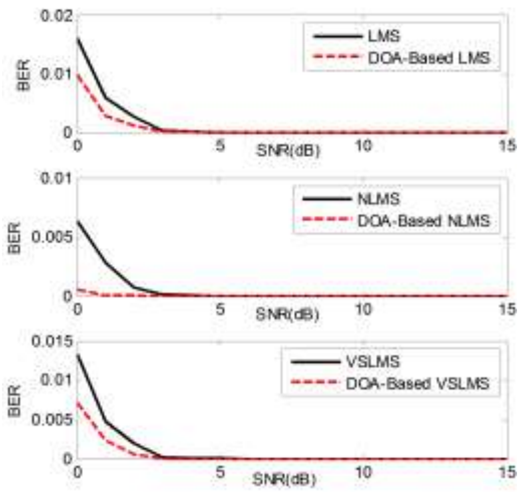

Fig. 11. BER changes when the desired DOA is in the centre of the initial beam

After the weight adjustment, data transmission begins. As depicted in Fig. 13, 14, the MSE of the transmitted data present lower levels for the DOA-based algorithms with respect to the conventional LMS, NLMS and VSLMS in all situations. Therefore, it can be concluded that convergence speed, efficiency and accuracy of the adaptive array are increased by using DOA-based LMS/NLMS/VSLMS.

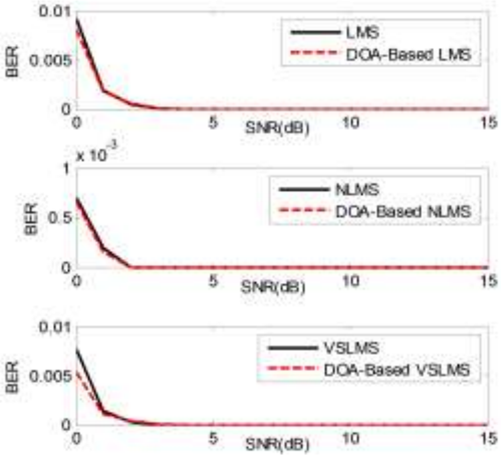

Fig. 12. BER changes when desired DOA is in the edge of the initial beam

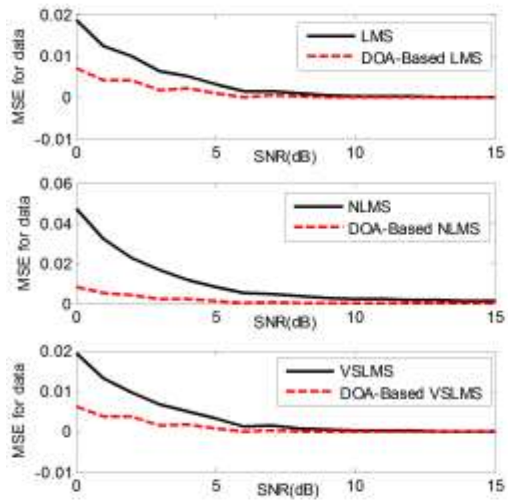

Fig. 13. MSE changes when the desired DOA is in the centre of the initial beam

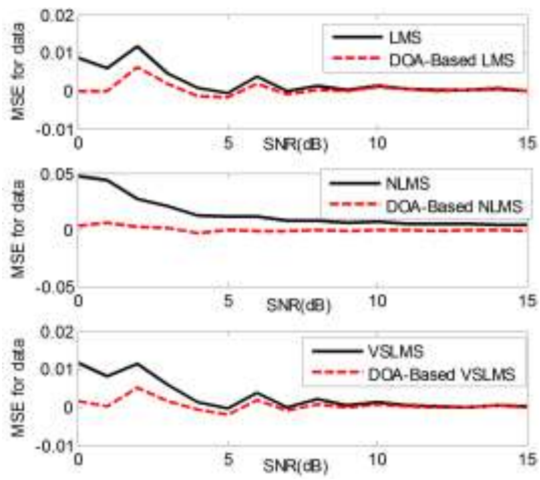

Fig. 14. MSE changes when the desired DOA is in the edge of the initial beam

In addition to the radiation pattern, convergence rate, MSE and SINR analysis, another term has been used for evaluating the performance of the proposed DOA-based LMS/NLMS/VSLMS algorithm compared to conventional one, namely Error Vector Magnitude (EVM) [15]. EVM is used for digitally modulated signals and measures the distortion introduced by the adaptive scheme on the received signal at a given SNR. $\mathrm{EVM_{RMS}}$ is defined as [15]:

$$\mathrm{EVM_{RMS}} = \sqrt{\frac{1}{\mathrm{KP_O}}\left|\sum_{j=1}^{K} S_r\,(j) - S_t(j)\right|^2} \qquad (12)$$

where K is the number of used symbols and P_O is the average power of all symbols for the given modulation. $S_t(j)$ and $S_r(j)$ are the j^{th} transmitted symbol and the j^{th} output of the beamformer, respectively. Figures 15, 16 show the $\mathrm{EVM_{RMS}}$ diagrams of the above-mentioned algorithms, conventional as well as proposed, for different values of input SNR ranging from 0–25 dB for two cases of DOA. EVM diagrams show close results in the transmission of symbols using LMS/NLMS/VSLMS beamforming schemes and DOA-based versions. This is reasonable because the mechanism of the algorithm has not changed. In DOA-based LMS/NLMS/VSLMS only the initial value of the weight vector has been changed so that the convergence rate increases.

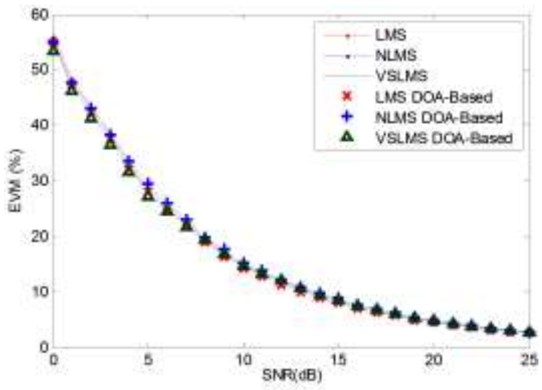

Fig. 15. EVM changes when the desired DOA is in the centre of the initial beam

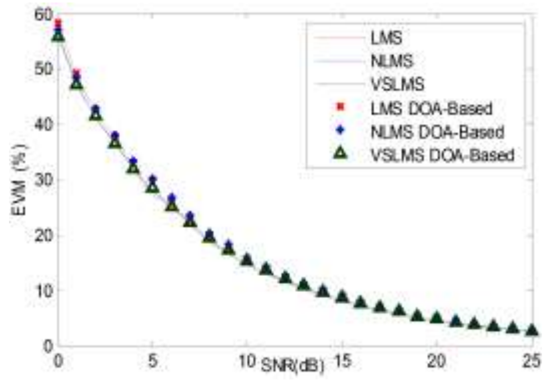

Fig. 16. EVM changes when the desired DOA is in the edge of the initial beam

Comparison of algorithms shows a larger computational cost for the DOA-based approach due to DOA estimation. This cost can be reduced by decreasing the resolution of the DOA estimation technique to a reasonable and sufficient value. In Table 1, the number of multiplications and additions for weight adjustment in the above simulated system is listed. The subspace-based DOA estimation methods such as the MUSIC also need Eigen-decomposition of the input covariance matrix for computation of the spatial spectrum. Consequently, in the DOA-based methods a better convergence speed and capability is obtained with a reasonable increase in the computational load. Utilizing a fast processor the proposed DOA-based algorithms can be converged in a short time while the LMS/NLMS/VSLMS cannot converge in that time even if a fast processor be available.

Table 1. Comparison of computational costs

Algorithm	Type of Instruction		
	×	+	/
LMS	1600	1600	-
NLMS	2400	2400	100
VSLMS	2600	3200	-
DOA-based LMS	6373	5448	37
DOA-based NLMS	7173	6248	137
DOA-based VSLMS	7373	7848	37

Two of the main advantages of the proposed method are lower error rate during adaption and better convergence and tracking speed. To investigate the tracking capability, in another simulation trial, the system is assumed to be time varying. The input SNR is 10 dB and the desired signal location is considered once in the centre of the initial beam at $\mathrm{DOA} = 25°$ and once in the edge of the fixed beam ($\mathrm{DOA} = 30°$). At iteration 4000 a variation in the system response causes an interruption in the adaptation. The proposed DOA-based methods offer better response in both centre and edge of the initial beam as the best and worst situation for beamforming. The MSE diagrams of this time varying system are demonstrated in Fig. 17, 18 for $\mathrm{DOA} = 25°$ and $\mathrm{DOA} = 30°$, respectively. An ideal response for DOA-based methods is observed in centre of the predetermined beam at $25°$. Variations of the MSE is less than the conventional LMS/NLMS/VSLMS in the variation time of system when the desired signal is at $30°$.

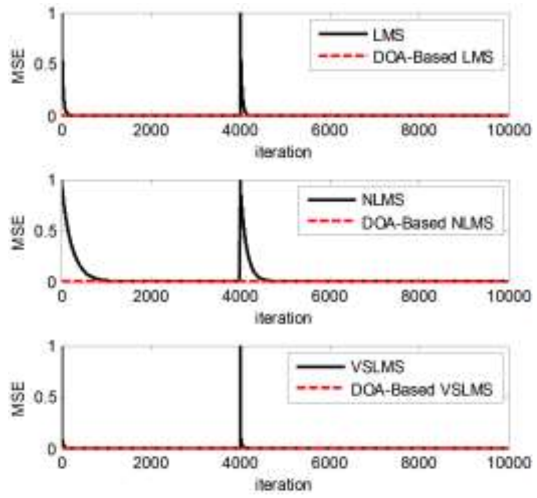

Fig. 17. MSE changes in time varying system when the desired DOA is in the centre of the initial beam

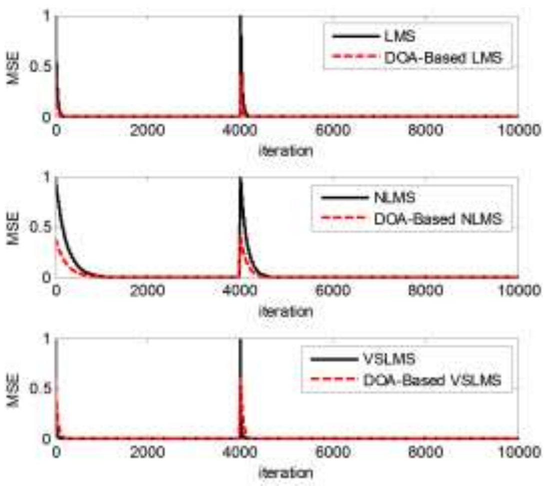

Fig. 18. MSE changes in time varying systems when the desired DOA is in the edge of the initial beam

The proposed method can be extended to the multi-beam applications. In such a condition, more initial states for joint beams should be considered in the preliminary adjustment and for any combination of M predetermined beams, corresponding to M signal sources, one weight vector is necessary to be calculated at the preliminary adjustment of the array. So, the total number of states of the initial value of the weight vectors will be increased but the beamforming time does not change.

Increasing the number of predefined beams leads to increase in accuracy and convergence rate. So, in order to achieve more accurate beamforming system, more initial narrower beams can be supposed and larger database will be obtained.

In addition to improvement of the LMS/NLMS/VSLMS adaptive algorithms, the proposed method has the advantage of interference nulling capability and higher accuracy than the switched beam technique. Other LMS-type algorithms can be improved using this approach, too. The algorithm also does not need hardware equipment required for conventional switched beam systems.

7. Conclusions

LMS, NLMS algorithms are common algorithms which are exploited for adaptive antenna beamforming. Despite simplicity, high stability and low computational complexity, LMS and NLMS algorithms take long times to converge leading to cause problems in mobile user tracking or adaptation with time-variant channels. In this paper a new spatial-temporal beamforming method is presented that exploits either common LMS or NLMS weighting algorithms and switched beam scheme in a joint state to increase the convergence speed and tracking capability of the conventional LMS or NLMS algorithms. Simulation results show an improved convergence and tracking speed while obtaining a higher efficiency and accuracy in data transmission through increased SINR and decreased BER and MSE. A reasonable increase in computational load occurs during DOA-based techniques which is practicable using signal processor unit.

It is important that the weight vectors obtained by the proposed DOA-based beamforming algorithms are closer than the final desired weight vectors compared to the conventional ones. It can be seen obviously in the comparative studies which are presented in terms of BER, SINR and MSE measures. In addition to the higher performances obtained by the proposed algorithms, faster convergence and also lower deviation in tracking study than the respected conventional ones are the main features of the proposed DOA-based beamforming algorithm. Hence, the type of algorithm cannot affect this issue. However, the results of variable step-size LMS (VSLMS) algorithm are added to the new version of paper. It should be noted that the speed increase will be obtained in the cost of computation of DOA information in VSLMS as well as conventional LMS and NLMS algorithms. Therefore, this result can be obtained in the other constrained or non-constrained LMS or LS family algorithms.

Also, low complexity DOA estimation algorithms can be applied to decrease the required computational complexity.

Recently, new antenna array geometry, Shirvani-Akbari array, is proposed for both DOA estimation and antenna array beamforming in the case of angles close to array endfires [28,29]. As a new work, Shirvani-Akbari array can be combined with the new idea of the present work to find better antenna beamforming in the case of angles close to array endfires.

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