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Beam Tracking Using Adaptive Algorithms for Single-Cell Massive MIMO Communication Systems

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Abstract: As communication base station beams toward users are getting narrower in millimetre-wave (mm-Wave) technology, a proper beam tracking system is required to follow the user mobility in 6G communication systems. Due to mobility, this task can be achieved via adaptive algorithms. To measure the performance of these algorithms, the metric of tracking speed and accuracy needs to be considered. In this paper, we study and compare the performance of multiple well-known adaptive algorithms such as the least mean squares (LMS), the normalized version of that (NLMS), and the recursive least squares (RLS) to track the narrow beam toward a user with a moving direction. The algorithms under investigation display a trade-off between convergence speed and tracking accuracy. Furthermore, in this paper, a bi-directional RLS tracking algorithm has been proposed called (BIRLS) to enhance the tracking accuracy. The high tracking accuracy can be a potential tool for new technologies such as intelligent reflection surfaces (IRS).

Keywords: *6G, Millimetre wave (mm-Wave), Least mean square (LMS), Recursive least square (RLS), bi-directional, Recursive least square (BIRLS).*

1 Introduction

The massive multiple input multiple output system (MIMO) has recently been employed in 5G to improve system efficiency and prevent interference from multiple input users by providing the base station with a large number of antennas (Almohammedi, 2019; Mahmood,2018). In 5G, the millimetre wave technology is used in conjunction with massive MIMO technology to meet the growing demand for great spectral efficiency and capacity. Estimating the direction of arrival (DoA) and beam-forming is an essential technology to track the users' signals via tracking the beam angles such that the desired user achieves the highest radiated power (Xia, 2020; Martinek, 2019; Sun, 2017; Chung, 2020; Lim, 2019; Prasad, 2017). In this paper, more than one adaptive algorithm is used and tested in Matlab, the simplest algorithm the least mean square (LMS) is characterized by its simplicity and low computational complexity (Martinek et al., 2019). The main drawback of LMS is the slow convergence; therefore, to solve this issue, normalization has been performed to obtain the normalized LMS (NLMS). The other algorithm used is the recursive least squares (RLS) algorithm to reduce the least-squares error associated with the signal recursively, thus providing an astonishing rate of convergence.

The researchers in (Prasad & Godbole, 2017) studied the effect of step size and the number of iterations on filter performance such as squared error, estimation accuracy, etc. The decrease in step size reduces steady-state error but at the same time increases convergence time, in (mm-wave) mobile communication case. The authors in (Rahman & Huq, 2015) show developed an adaptive noise cancelling device by applying (LMS) and (NLMS) algorithms. Because (LMS) has a fixed step size, it is not suitable for working in an unstable environment.

But for (NLMS), is suitable for working in an unstable environment as well as a static environment. The researchers in (Patel et al., 2016) used algorithms least mean square (LMS), Sample matrix inversion (SMI), Recursive least square (RLS). It was observed that with an increase in the number of elements, an improvement in beam width and reduced interference between users could be

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obtained. The work in (Va et al., 2016) proposed the Kalman beam tracking algorithm as a solution to reduce beam training overhead. An interesting effect was the size of the matrix. At the same SNR, the array must be chosen to be large enough for optimal performance. The authors in (Yapıcı & Güvenç, 2018) show derived the (LMS) algorithm and Bidirectional least mean square (BILMS) extension algorithm is derived from the steeper main algorithm. The numerical results show that (LMS) and (BILMS) rapidly converge with the best performance for increased SNR. On the other hand, with an increasing SNR the RLS algorithm exhibits a relatively slow convergence.

The performance of the tracking algorithm, which is usually restricted by the step size and the number of iterations, is measured by the minimum mean square error MSE, the cost function, and the convergence time.

In the case of (mm-Wave) mobile communication, a smaller step size reduces steady-state error whereas increasing convergence time.

In this paper, we proposed a bidirectional RLS (BIRLS) algorithm to increase accuracy and to estimate in a frequency selective channel. The algorithm requires both the forward- and backward-channel states, as the initial value of the channel information must be available to process the bidirectional algorithm. Channel information includes the path gain, departure, and arrival angles (channel path gains, Angle of a river (AoA), Angle of departure (AoD) to start the adaptive process in the back direction.

The rest of the paper is organized starting from Section II where the system model is introduced, Section III, the adaptive algorithms are derived, and in Section IV, our proposed algorithm numerical results are presented.

2 The System Parameters

The channel parameters will be discussed in this section, which includes the beam forming model and the channel observation.

2.1 The Mm Wave Channel Model

The geometric channel model of the (mm-Wave) time-varying channel is used with path=L, which represents the communication path between the mobile transmitter and the base station receiver with a range of one to L paths. The channel's geometric time-varying expressing can be indexed with time *(k)* as (Yapıcı & Güvenç, 2018):

$$\boldsymbol{H}_k = \sum_{l=1}^{L} \boldsymbol{\alpha}_{k,l}\boldsymbol{a}_R(\theta_{k,l})\boldsymbol{a}_{\boldsymbol{T}}(\Phi_{k,l})^T, \qquad (1)$$

The value l is the number of wireless paths between 1 and L. $\boldsymbol{\alpha}_{k,l}$ is the complex path gain, $\theta_{k,l}$ is the angle of departure of the channel and $\Phi_{k,l}$ is the angle of arrival to the receiver in the base station. The transmit array $a_T(.)$ and the receive array $a_R(.)$, which are the response vectors in the channel, can be expressed as

$$\boldsymbol{a}_R(\theta) = \frac{1}{\sqrt{M}}[1 \;\; e^{-2j\pi\frac{d}{\lambda}\cos(\theta)} \; .... \; e^{-j2\pi\frac{d}{\lambda}(M-1)\cos(\theta)} \;]^T, \qquad (2)$$

$$\boldsymbol{a}_T(\Phi) = \frac{1}{\sqrt{N}}[1 \;\; e^{-2j\pi\frac{d}{\lambda}\cos(\Phi)} \; .... \; e^{-j2\pi\frac{d}{\lambda}(N-1)\cos(\Phi)} \;]^T, \qquad (3)$$

The wavelength is λ, in a uniform linear array (ULA), d is the spacing of the antenna, the number of transmitter antennas is N. The number of receiver antennas is M, where $[.]^T$ is the transpose of $[.]$.

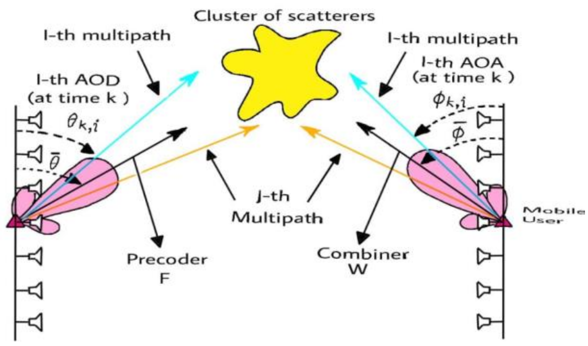

Figure.1: Precoder and combiner vector for the mmWave mobile communication system and the scatter angle of the clusters.

To simulate the real channel that we desire to track, the evolution of time of the complex path gain is modelled via the first-order regression approach as follow (Yapıcı & Güvenç, 2018):

$$\boldsymbol{\alpha}_{(k+1)} = \rho\boldsymbol{\alpha}_k + \boldsymbol{u}_k^{\alpha}, \qquad (4)$$

$\boldsymbol{\alpha}_k$ is the complex path gain vector of the complex path for all the multiple paths $\boldsymbol{\alpha}_k = [\boldsymbol{\alpha}_{k,1} \; \alpha_{k,2} \; ..... \; \boldsymbol{\alpha}_{k,L}]^T$, the distribution of this path is a zero-mean complex Gaussian with a variance matrix of $(1-\rho^2)\boldsymbol{I}_L$, where I_L is the identity matrix with a size equal to$L$, the respective noise of innovation $\boldsymbol{u}_k^{\alpha}$, the correlation of coefficient is ρ .In addition, the following is how the angular fluctuation over time is modelled as Gaussian noise:

$$\boldsymbol{\theta}_{(k+1)} = \boldsymbol{\theta}_k + \boldsymbol{u}_k^{\theta}, \qquad (5)$$

$$\boldsymbol{\Phi}_{(k+1)} = \boldsymbol{\Phi}_k + \boldsymbol{u}_k^{\Phi}, \qquad (6)$$

Where:

$\boldsymbol{\theta}_k = [\boldsymbol{\theta}_{k,1} \; \boldsymbol{\theta}_{k,2} \; ..... \; \boldsymbol{\theta}_{k,L} \;]^T$ and

$\boldsymbol{\Phi}_k = \ [\boldsymbol{\Phi}_{k,1}\ \boldsymbol{\Phi}_{k,2} \dots . . \boldsymbol{\Phi}_{k,L}\ ]^T$

Also, follow independent zero-mean complex Gaussian processes with covariance processes $\sigma_\theta^2 I_L$ and $\sigma_\Phi^2 I_L$ with $\boldsymbol{u}_k^\Phi$ (Patel, 2016; Va, 2016).

2.2 Beam forming Model

The antenna gain depends on the direction of transmission and reception of the signal. Thus, to have a large gain towards the desired direction, one has to rotate the antenna towards that angle. To overcome this problem, we can use the technology beam forming. In this paper a full analog transceiver is considered with a receive combiner w and a transmit precoder f as shown in fig. (1), the precoder and combiner can be expressed as:

$$\boldsymbol{f} = \frac{1}{\sqrt{M}}\ [1\ \ e^{-2j\pi\frac{d}{\lambda}\cos\bar{\theta}}\ \dots \dots . e^{-j2\pi\frac{d}{\lambda}(M-1)\cos\bar{\theta}}]^T, \quad (8)$$

$$\boldsymbol{w} = \frac{1}{\sqrt{N}}\ [1\ \ e^{-2j\pi\frac{d}{\lambda}\cos\bar{\boldsymbol{\Phi}}}\ \dots \dots . e^{-j2\pi\frac{d}{\lambda}(N-1)\cos\bar{\boldsymbol{\Phi}}}\ ]^T, \quad (9)$$

$\bar{\boldsymbol{\theta}}$, represents the direction (precoder $\boldsymbol{f}$) of the beam, and $\bar{\boldsymbol{\Phi}}$ represents the direction of the collector ($\mathbf{w}$) of the beam.

3 Tracking Via Adaptive filters

Adaptive filters are self-designed systems that operate in environments without knowledge of statistical information and rely on iterative algorithms. This section introduces algorithms (LMS, NLMS, and RLS) for estimating unknown (mm-wave) channel parameters AoA, AoD, and path gains.

3.1 Least Mean Square Algorithm (LMS)

In 1960, the two scientists (Widrow and Hoff) derived an algorithm they called: the least mean square LMS algorithm. It belongs to the stochastic gradient algorithm because it usually estimates the gradient vector from the steepest descent methods (SDM) with a random vector, with the filter parameters being updated to meet with the optimal solution is characterized by its simplicity and low computational complexity (Jose, 2016). LMS technique is used here to adaptively follow the states $\mathrm{x_k}$ instead of using the weights. The states represent the observed channel states including the complex gains: the real gain α_R and the imaginary α_I as well as the beam directions.

$$\boldsymbol{x}_k = [\boldsymbol{\alpha}_{R,k}^T\ \ \boldsymbol{\alpha}_{I,k}^T\ \ \boldsymbol{\theta}_k^T\ \ \ \boldsymbol{\Phi}_k^T\ \ ]$$

We will look at the LMS algorithm in the state vector $\boldsymbol{x}_k$ first to track the communication beam adaptively. The steepest descent algorithm, which is the optimum algorithm in this sense, is used in LMS to converge in the nonlinear environment (Yapıcı & Güvenç, 2018):

$$\hat{\boldsymbol{x}}_{(k+1)} = \hat{\boldsymbol{x}}_k - \mu \boldsymbol{\nabla}_{\hat{x}_k} J_k, \quad (7)$$

$\hat{\mathrm{x}}_\mathrm{k}$ is the estimation of $\mathrm{x_k}$, we reflect the algorithm's adaptation step size (μ) in equation (7) by diagonal matrix $\mu = [\mu_\alpha 1_{2L}\ \ \mu_\theta 1_L\ \mu_\Phi 1_L]$,

μ_α, μ_θ and μ_Φ represent the particular channel path gain, AoD, AoA respectively, $\nabla_{\hat{x}_k}$ is the gradient operator, $\mathrm{J_k}$ is the mean square error at time k.

The estimation error is $\mathrm{e_{(k)} = y_{(k)} - h_{(\hat{x}_k)}}$, have a real part $\mathrm{e_{R,k}}$ and an imaginary part $\mathrm{e_{I,k}}$, the MSE gave as

$\mathrm{J_k = E\{\|e_k\|^2\}}$ with $\mathrm{e_k = [e_{R,k}\ e_{I,k}]^T}$

The cost function can be expressed as (Yapıcı & Güvenç, 2018):

$$\text{cost function} = \operatorname{argmin}(\mathrm{J_k})$$

The gradient of the MSE is given as:

$$\boldsymbol{\nabla}_{\hat{x}_k} J_k = -2\boldsymbol{e}_k^T \frac{\partial \boldsymbol{h}(\hat{\boldsymbol{x}}_k)}{\partial \hat{\boldsymbol{x}}_k} \quad (10)$$

$$\boldsymbol{\nabla}_k = \frac{\partial h_{(\hat{x}_k)}}{\partial \hat{x}_k} \quad (11)$$

$$\hat{\boldsymbol{x}}_{(k+1)} = \hat{\boldsymbol{x}}_k + 2\boldsymbol{\mu}\boldsymbol{e}_k^T \boldsymbol{\nabla}_k \quad (12)$$

$\boldsymbol{\mu}$, is step size.

3.2 Normalized least mean square algorithm (NLMS)

Another adaptive algorithm that can be considered as an enhancement on LMS is normalized LMS (NLMS) to achieve higher convergence speed and better minimum mean square error than LMS.

As it is difficult to select the learning rate NLMS provides a better way to ensure stability faster and more accurately (Rahman & Huq, 2015).

Normalization of input vectors allows NLMS to solve problems by adjusting the step size to the state of the vector status.

$$\hat{\boldsymbol{x}}_{(k+1)} = \hat{\boldsymbol{x}}_k + \frac{1}{\|\boldsymbol{x}_k\|^2}\ \boldsymbol{e}_k^T\ \boldsymbol{\nabla}_k, \quad (13)$$

The step size *of* the adaptive filter is μ, the normalization norm vector of $\boldsymbol{x}_k$ is $\|\boldsymbol{x}_k\|^2$.

3.3 Recursive Least Square Algorithm (RLS)

A very important adaptive filter algorithm is the Recursive least squares RLS algorithm. The RLS for strongly interrelated input signals has a higher convergence rate compared to LMS. The computational complexity is much greater. The algorithm RLS has excellent performance when operating in an evolving environment over time, but at the cost of increased computational complexity and some stability problems due to matrix inversion (Rahman & Huq, 2015).

$$\hat{\boldsymbol{x}}_{(k+1)} = \hat{\boldsymbol{x}}_{(k)} + \boldsymbol{e}^{T}_{k\,(k)} \boldsymbol{kf}_{(k)}, \qquad (14)$$

$\boldsymbol{kf}_{(k)}$ is the filter coefficient vector.

$$\boldsymbol{kf}_{(k)} = \boldsymbol{P}_k \, \boldsymbol{\nabla}'_k \, \frac{1}{F_f + \nabla_k \boldsymbol{P}_k \, \nabla'_k} \;, \qquad (15)$$

F_f –is a forgetting factor between 0 and 1.
$\boldsymbol{P}_k$ –the estimation covariance.

$$\boldsymbol{P}_{(k+1)} = (I - \boldsymbol{kf}_{(k)} \, \boldsymbol{\nabla}_k) \, \boldsymbol{P}_k \qquad (16)$$

3.4 The Proposed Algorithm (Bi-Direction Recursive Least Squares (BIRLS)

Estimating receiver (DoA) direction of arrival and beam forming is a core technology that aims to estimate users' signals and reduce interference so that the radiated power toward the desired users is maximized, so successful design depends on the selection of the estimation algorithm, which must be very accurate and robust. An estimation algorithm with better performance than bidirectional (LMS, NLMS, and RLS) algorithms (BIRLS) is proposed to estimate fast frequency-selective variable channels in the forward and reverse directions. The tracking performance of the proposed algorithm in steady-state is very close to the minimum squared optimum error.

3.5 Derivation of the proposed bidirectional algorithm (BIRLS)

The proposed algorithm (BIRLS) is bidirectional, an extension of the iterative algorithm RLS unidirectional; the proposed algorithm works in both forward and backward directions for packet tracking and channel estimation over time in a wireless communication environment, for adaptive state tracking, a vector can be represented case ($\mathbf{x}_k$) which includes the real channel gain, imaginary channel gain, departure angle (AoD), and angle of arrival (AoA) as follow:

$$\boldsymbol{x}_k = \left[\boldsymbol{\alpha}^{T}_{R,k} \;\; \boldsymbol{\alpha}^{T}_{I,k} \;\; \boldsymbol{\theta}^{T}_{k} \;\; \boldsymbol{\Phi}^{T}_{k}\right] \qquad (17)$$

The proposed algorithm (BIRLS) estimates the forward and backward channels along the observation block. The estimation equation for the proposed algorithm (BIRLS) in the forward direction is given as follows:

$$\hat{\boldsymbol{x}}^{f}_{(k)} = \hat{\boldsymbol{x}}^{f}_{(k-1)} + \boldsymbol{e}^{f'}_{k} \, \boldsymbol{kf}^{f}, \qquad (18)$$

$\hat{\boldsymbol{x}}^{f}_{(k)}$: The vector is estimated in the forward direction, i.e. the back value.

The channel estimation in the backward direction can be represented as follows.

$\boldsymbol{e}^{f'}_{k}$: The estimated error in the forward direction.
$\boldsymbol{kf}^{f}$: Forward vector gain.

The channel estimation in the backward direction can be represented as follows.

$$\hat{\boldsymbol{x}}^{b}_{(k-2)} = \hat{\boldsymbol{x}}^{b}_{(k-1)} + \boldsymbol{e}^{b'}_{k} \, \boldsymbol{kf}^{b} \qquad (19)$$

Where:
$\hat{\boldsymbol{x}}^{b}_{(k-2)}$: The vector represents the estimated posterior direction, meaning the previous value.
$\boldsymbol{e}^{b'}_{k}$: Estimated backward error.
$\boldsymbol{kf}^{b}$: Backward gain.

The final grading coefficient $\hat{\mathbf{x}}_k$ can be obtained as follows:

$$\hat{\boldsymbol{x}}_k = \frac{\hat{x}^{f}_{(k)} + \hat{\boldsymbol{x}}^{b}_{(k-2)}}{2} \qquad (20)$$

The proposed algorithm (BIRLS) is characterized by a faster convergence than the RLS algorithm in a rapidly changing environment and gives tracking and estimation results in both forward and backward directions, characterized by high computational cost, and the performance of the proposed algorithm in the steady-state is very close to the minimum optimum mean square error (MSE).

4. Numerical Results and Discussion

In this part, the performance of the algorithms understudy will be tested for (mm-Wave) beam tracking. Multiple antennas with N=M=16, and SNR= 30dB, for a narrow physical beam, will be assumed. we also assume that the multipath L=1, which is quite likely. The distance between the antennas is d=0.9cm, and the temporal angles of the channel for (mm-Wave) are considered to be 0.995 and $\sigma^2_\theta = \sigma^2_\Phi = 0.1^2$. We also consider an arbitrary vector direction of ($\bar{\theta} = \bar{\Phi} = 45^\circ$). The step size for the adaptive process will be regulated as $\mu_\alpha = 0.1$ and $\mu_\theta = \mu_\Phi = 0.0001$, which will be converted to rad for consistency purposes, and the wavelength $\lambda = 9$ mm.

5 The Results and Discussion

It is clear from the comparison of the LMS algorithm in Figure (2) after simulating it with the MATLAB program that the adaptive algorithm LMS needs large step size values (step size) to obtain the steady-state, where at the value of step size (μ=0.1) The algorithm LMS showed faster convergence and a lower cost function, which means that the mean square error (MSE) is less and therefore gives a more accurate estimate.

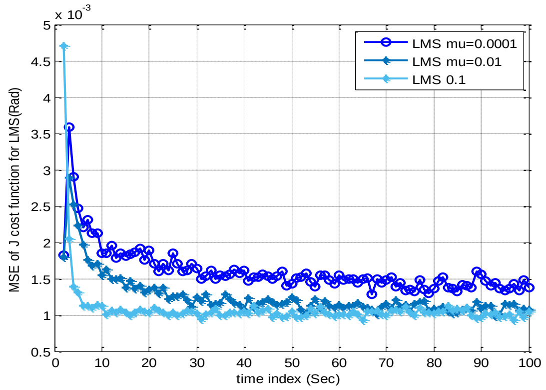

Figure 2: Comparison of algorithm performance (LMS) at different step size values.

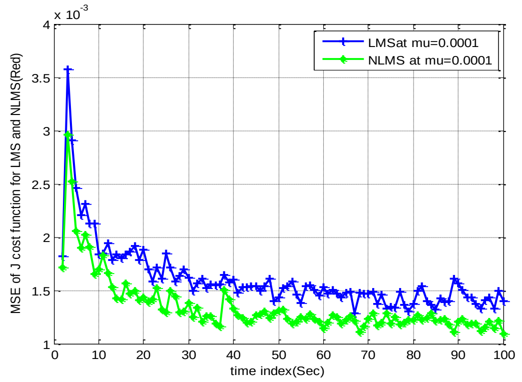

Figure 3: Compare performance between (LMS and NLMS) algorithms.

In Figure (3) it can be seen that the NLMS algorithm gives better performance to track and estimate channel state than the LMS algorithm due to the adaptive step size, as it gives greater stability with changing signals.

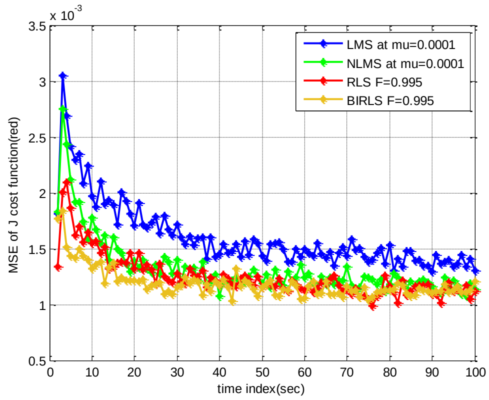

Figure 4: Comparison of the performance of the proposed algorithm (BIRLS) and algorithms (LMS, NLMS, RLS).

In Fig. (4) After comparing the performance of algorithms (LMS, NLMS, RLS) in terms of accuracy of estimating time-varying channel state (User) in millimetre waves of Massive MIMO, there was a need to propose an algorithm that gives better tracking and estimation performance than previous algorithms. The proposed Bi-Directional Algorithm (BIRLS) gives better tracking and estimation performance than (LMS, NLMS, RLS) algorithms, with lower error rate, and this helps to obtain higher accuracy in user packet tracking and channel status estimation in a rapidly changing environment.

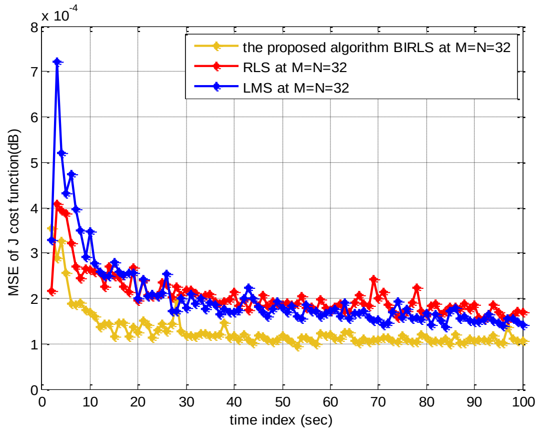

Figure 5: A comparison of the performance of (BIRLS) algorithm with two algorithms (LMS, RLS).

In Fig. (5) with the number of antennas (M=N=32), and using the same step size value (μ=0.0001), it can be seen that the BIRLS algorithm has a faster convergence rate than the two algorithms (RLS, LMS), and gives the lowest error ratio between the desired signal and the filter output. Therefore, using the BIRLS algorithm, beam tracking, and channel estimation accuracy is more efficient.

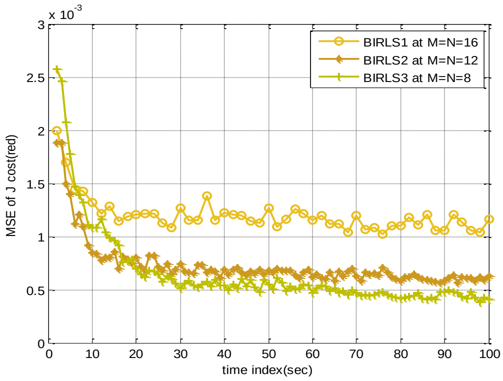

Figure 6: a comparison of the proposed algorithm (BIRLS) at different values of array size.

The performance of the proposed bidirectional algorithm (BIRLS) was compared with different values of the array size, and it was noted that the small array is insensitive to changes in the departure angle AoD and the angle of arrival AoA, while the large transmit and receive arrays are more sensitive to angular changes and give better tracking accuracy.

6 Conclusions

In this paper, we used adaptive algorithms (LMS, NLMS, and RLS) to study channel tracking and adaptive beam generation. A non-linear control model was used to construct the strategies. We have proposed an algorithm with better tracking performance than (LMS, NLMS, RLS) algorithms which is the bi-direction (BIRLS) for estimating time-varying channels, which is an extension of the unidirectional RLS algorithm, the proposed algorithm reduces the error ratio of the angle difference between the test and the estimated signal. Furthermore, the proposed algorithm (BIRLS) can estimate channels in a rapidly changing environment for the radio user channel in both forward and backward directions.

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