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DESIGN OF MILLIMETER-WAVE BEAMFORMING FOR 5G COMMUNICATION ANTENNAS

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Abstract
A smart antenna is actually combination of an array of individual antenna elements and dedicated signal processing algorithm. With this technology, each user's signal is transmitted and received by the base station only in the direction of that particular user. The direction of arrival (DOA) estimation and beamforming are effective methods for spatial diversity realization. Various algorithms already exists for implementing these methods. Various sample-by-sample methods, attempted in the present study are least mean square (LMS) algorithm, recursive least square (RLS) algorithm. This paper explores the performance of least mean square (LMS) and recursive least square (RLS) beamforming algorithm. It would be demonstrated through simulation that RLS algorithm increases signal quality by elimination interfering signals and noise by nulling them, while sending maximum signal (beams) to the desired direction. The simulation is performed using matlab software tool.

Keywords:
Smart Antenna, Beamforming, LMS, RLS

1. Introduction

Recently and over the last decade, the wireless and mobile technologies in addition to the new and improved services have grown rapidly at exponential and formidable rate. In the evolution of the modern telecommunication networks and multiple access systems, the employment of the spatial processing approaches and techniques becomes essential according to the related standards. The spatial processing is considered as the main idea behind the use of adaptive and smart antennas, antenna arrays, beamforming algorithms, interference cancelation, bandwidth-efficient signaling systems, and direction of arrival (DOA) estimation schemes (in the case of non-blind beamforming).

Smart antenna system basically consists of multiple antennas or antenna arrays and digital signal processing algorithms that are in charge of very important functions such as DOA estimation of the signals. In general, the wireless communication systems development stages can be classified based on the adopted technologies driven by the challenges of capacity demand

and quality of service (QoS) requirements. These stages are summarized as follows [1]:

- Omni-directional systems: with conventional cellular structure, frequency reuse (7 cells reuse patterns), Omni-directional antenna types in the base station at the center of each cell.
- Cell splitting and sectorized systems: smaller cells (micro-cells), cell sectoring with several directional antennas in the base station.
- Smart antenna systems: with dynamic cell sectorization, multiple antennas (antenna arrays), innovative signal processing algorithms, and beamforming techniques (user location based beam assignment).

In general, beamforming techniques are grouped by three types including analog, digital and hybrid beamforming [2] and [3]. In 5G base station, the digital and hybrid beamforming techniques are commonly used to reduce power consumption that is proportional to the number of antenna element in the array. As the massive MIMO with a large number of antenna elements, so that the main challenge for fully digital beamforming in 5G gNodeB is the low computational of beamforming and reduced number of Sounding Reference Signal (SRS).

Therefore, the non-blind adaptive beamforming is a good candidate for gNodeB. A beamformer consists of two main parts: DOA estimation and beamforming. DOA is necessary to estimate accurately the incoming signal equivalent to the direction of radio waves from the UE. After the broadcast phase, depending on the number of present UEs, a corresponding number of desired main beams are generated corresponding with the UE locations using adaptive beamforming techniques such that each desired beam is steered towards the associated UE. During the process of creating a beam, we need to control sidelobe level. When the sidelobe level (SLL) is too high, it will reduce the main beam's energy. Some commonly non-blind algorithms are: least-meansquare (LMS) algorithm, the recursive-least-square (RLS) algorithm, sample matrix inversion (SMI), and conjugate gradient (CG) [4]. Among them, RLS algorithm has the best beamforming in term of convergence speed [5].

Adaptive beamforming is a particular interest of 5G because it provides a great advantage and benefits. It can boost its throughput, high spectral and energy efficiency by increasing its Signal-to-interference ratio (SIR) and the signal-to-noise-ratio (SNR) by nulling noise or interference sources and directing maximum signals to source of interest. Hence the need for this paper which looks at technique to apply adaptive beamforming with mmWave and massive MIMO to boost throughput and signal quality by eliminating interfering signal (i.e. other parallel UEs) and noise associated with communication system to increase the SINR.

2. Smart antenna systems

The aforementioned smart antenna systems are widely implemented in two forms, namely, the switched beam approach where the system can choose one of many predefined antenna beam patterns (the antenna radiation or propagation pattern is defined as graphical representation of the power variation and radiation properties of the antenna as a function of the direction and space coordinates), and the adaptive array approach where the antenna adapts the radiation pattern beams in real time in accordance with the radio environment.

The smart antennas systems achieve higher capacity increase in comparison with the switched beam systems especially in the case of densely populated coverage areas and reduce more effectively the negative impacts of the interference. Additionally, there are more advantages that can be counted in favor of adaptive array systems such as range increasing, security enhancement (more difficult to tap any connection) [6], and location-based services improvements especially for emergency situations (spatial detection characteristics). As in the case of any system or technology, some disadvantages or drawbacks of the smart antenna systems are found like the complexity of transmitters and receivers design, the high computation intensity with the need of powerful digital signal processors (DSPs), and the overall system employment cost. At this point, two fundamental objectives should be performed by the signal processing algorithms of the smart antenna systems, namely:

- The DOA estimation for all incoming signals;
- Adaptive real-time calculation of the weights or coefficients that are used to steer and change the directions of the antenna array radiation beams toward the signal-of-interest (SOI) and at the same time to place nulls toward the signal-non-of-interest (SNOI) that is considered as interfering signal.

Hence, the smart antennas systems relay on the adaptive signal processing techniques such as DOA estimation and adaptive beamforming under the use of multiple antenna configurations (antenna arrays).

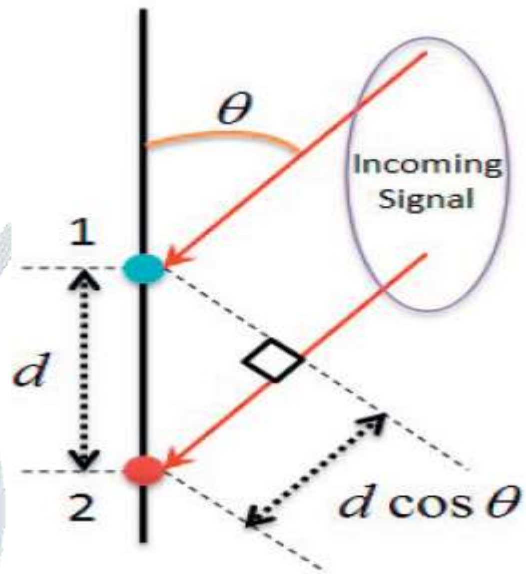

Fig1. DOA main concept

3. Adaptive Beamforming Theory

The information generated from and accumulated from an antenna can be referred to as beam. It can be highly directive or omni-directional (all directions). Most of the useful signal is carried by the main lobe (useful signal) while the side-lobes are interfering signals. Beamforming or spatial filtering technique using various algorithms are used to direct or point radiation from multiple radiating elements to a particular or more directive direction.

Adaptive beamforming provides better beam steering system because of their ability to adapt in real time to the changing electromagnetic environment. They use digital signal processing to dynamically update weights to meet changing signal environment in other to direct signal-of interest towards the pilot while suppressing the interferers. With spatial division multiple access, multiple useful beams can be created within a communication system and allocated to different users with only an angle separation [7].

In adaptive beamforming, complex weights are computed adaptively in a digital signal processor using an adaptive technology that generate an array factor for an optimal signal to- interference and noise ratio (SINR). This results in a pattern where the target signal which is the maximum of the pattern is directed towards the targeted user while nulling the interferers.

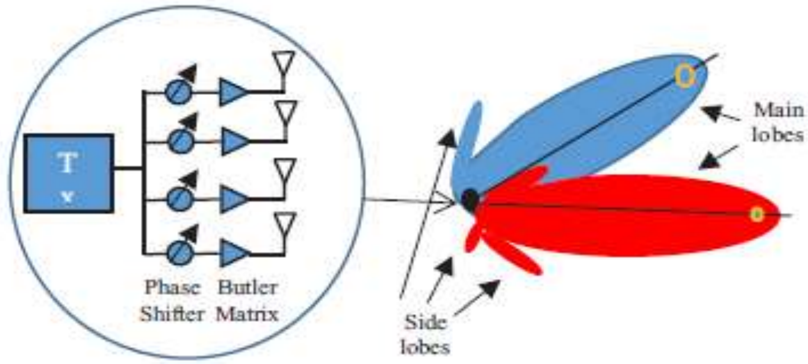

Fig2: Beamforming using four transmit

For the millimeter wave (mmWave) systems, almost all modern wireless communication networks, the antenna BF shows great benefits since highly directional adaptive antenna array elements can be designed with low profile and steering capabilities in various directions to meet and coherently align the SOIs and dampen the undesired or interfering signals (SNOIs).

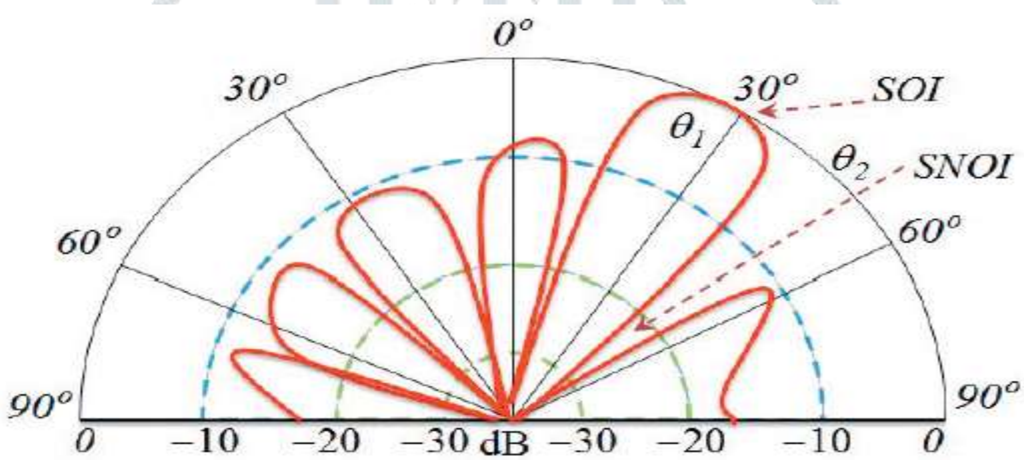

Fig3. Antenna radiation pattern of linear antenna array with M = 8 identical elements and BF technique

In Fig3, a normalized radiation pattern of linear antenna array with eight identical elements (M = 8) and equal spacing is presented. It is shown that by employing BF technique, the major beam (main lobe) is directed toward the SOI ($\theta 1 = 30°$), and a null is placed tow ard the SNOI ($\theta 2 \approx 50°$).

Consider a uniform linear array (ULA) of fig. 4. composing of M- elements, the number of narrowband plan waves represented by L, centred at centre frequency f_0 which impinges on the ULA from directions $(\theta_1, \theta_2, \ldots\ldots, \theta_l)$

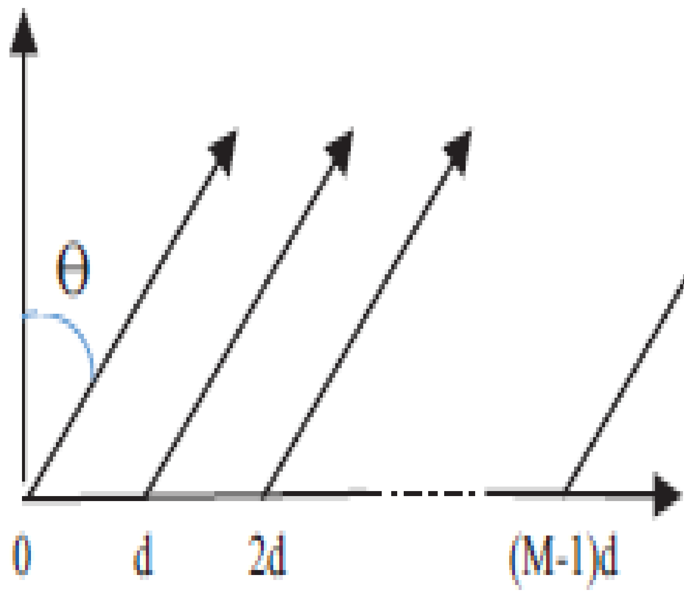

Fig4: Uniform M-Element Linear Array

LMS

This algorithm was first developed by Widrow and Hoff in 1960 [8-9].The design of this algorithm was stimulated by the Wiener-Hopf equation. By modifying the set of Wiener-Hopf equations with the stochastic gradient approach, a simple adaptive algorithm that can be updated recursively was developed. This algorithm was later on known as the least-mean-square (LMS) algorithm [8]. The algorithm contains three steps in each recursion: the computation of the processed signal with the current set of weights, the generation of the error between the processed signal and the desired signal, and the adjustment of the weights with the new error information. The following equations summarize the above three steps.

$\hat{d}(n) = w_1^*(n)u_1(n) + w_2^*(n)u_2(n) + \cdots \ldots. + w_t^*(n)u_t(n)$

The $\boldsymbol{w}$ in the above equations is a vector which contains the whole set of weights.

Here, we have taken eight elements, so there are eight $u's$ for each symbol received at time n. A large step-size allows fast settling but causes poor steady state performance. On the other hand, a

small step-size decreases the steady state error but compromises the rate of convergence. The current value of this parameter is selected by trying out different values in the algorithm.

RLS

The RLS algorithm[9] recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals, i.e., given the least squares estimate of the tap weight vector of the filter at iteration (n-1),we compute the updated estimate of the vector at iteration n upon the arrival of the new data. This, in contrast to LMS algorithm aims to reduce the mean square error. In the derivation of the RLS, the input signals are considered deterministic, while for the LMS, they are considered stochastic. Compared to most of its competitors, the RLS exhibits extremely fast convergence due to the fact that the RLS filter

whitens the input data by using the inverse correlation matrix of the data, assumed to be of

zero mean. However, this benefit comes at the cost of high computational complexity.

The RLS algorithm can be summarized as follows,

Initialize the algorithm by setting

$\hat{w}\,(0) = 0, P(0) = \delta^{-1}\, I$

δ= large positive constant for low SNR, small positive constant for high SNR

For each instant of time, n=1,2,….

$\pi(n) = P(n-1)u(n)$

$k(n) = \frac{\pi(n)}{\lambda + U^H \pi(n)}$

$\xi(n) = d(n) - \widehat{w}\, H(n-1)u(n)$

$\widehat{w}(n) = \widehat{w}\, H(n-1) + k(n)\xi * (n)$ and

$P(n) = \lambda^{-1}p(n-1) - \lambda^{-1}k(n)u^H(n)P(n-1)$

4. Antenna Design and Simulation

In this section, the performance of adaptive beam-former is implemented using RLS, least mean square (LMS) and minimum variance distortion less response (MVDR) algorithm to determine the optimum array weights and to point a null of the array response in the direction of an interfering source. Here it is initially assumed that all signals arriving at the antenna element are monochromatic. Also assumed is that the total number of signals arriving is less than the antenna elements. The initial conditions were chosen as per 5G requirements of 28 GHz. An 8-element uniform linear array (ULA) with half wavelength $\left(\frac{\lambda}{2}\right)$ element spacing, carrier frequency of 28 GHz. The desired signal will be assumed to be incident on the ULA from an azimuth angle of $\theta_s = 15^\circ$ and an interfering signal arriving at $\theta_i = 60^\circ$ respectively. The channel is simulated in the presence of complex white Gaussian noise, and assuming a noise power of 0.5watts (corresponds to 3dB SNR) at each antenna element. The RLS, LMS and MVDR algorithm were used to place nulls in the antenna pattern and implemented using Matlab simulation software.

5. Results and Discussion

Fig5 shows the magnitude of the weight vs iteration number. It also shows that as the number of antenna element increases, the weights converge as the number of iteration increases using the RLS algorithm and compared with LMS algorithm.

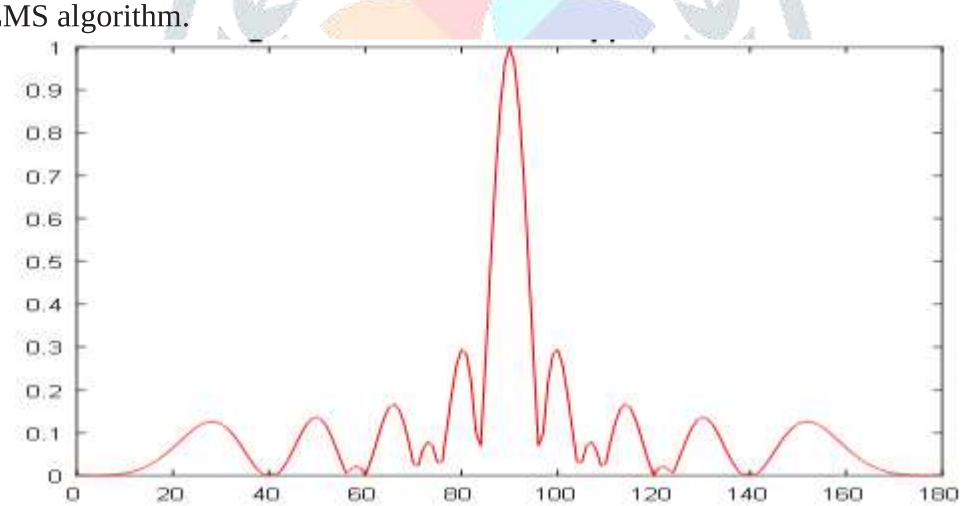

Fig5. Weighted LMS and RLS array pattern for N=8

How the array output acquires and track the desire signals is shown in figures 6. The two plots shows that the RLS algorithm array output was able to acquire and track the signal after about 60 iterations, but was not possible with LMS algorithm.

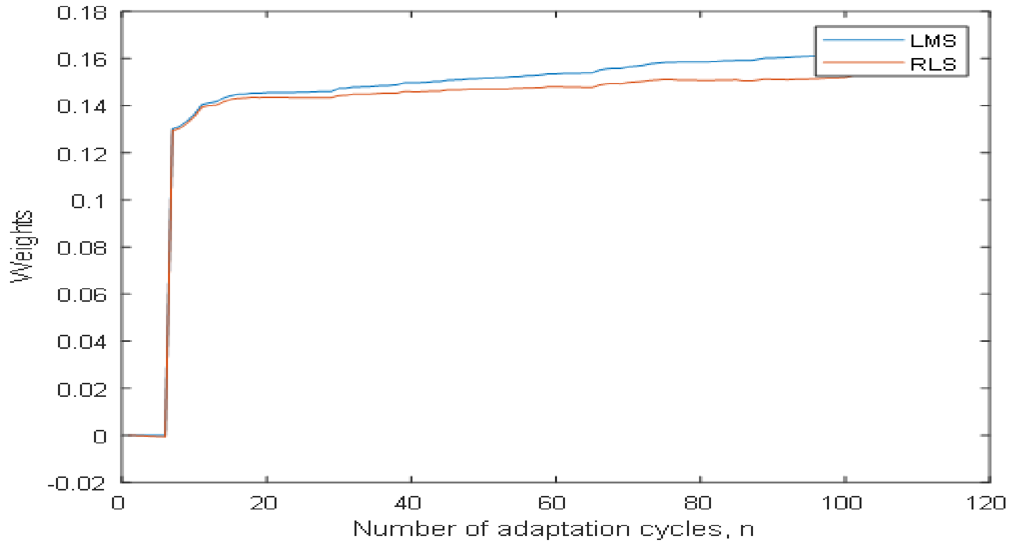

Fig6. Magnitude of array weights for N=8

Figure 7 shows using RLS and LMS algorithm, the resulting mean square error (MSE) that converges to stable state after 0.2 adaption cycles for RLS and converges to stable state after 0.8 number of adaption cycles.

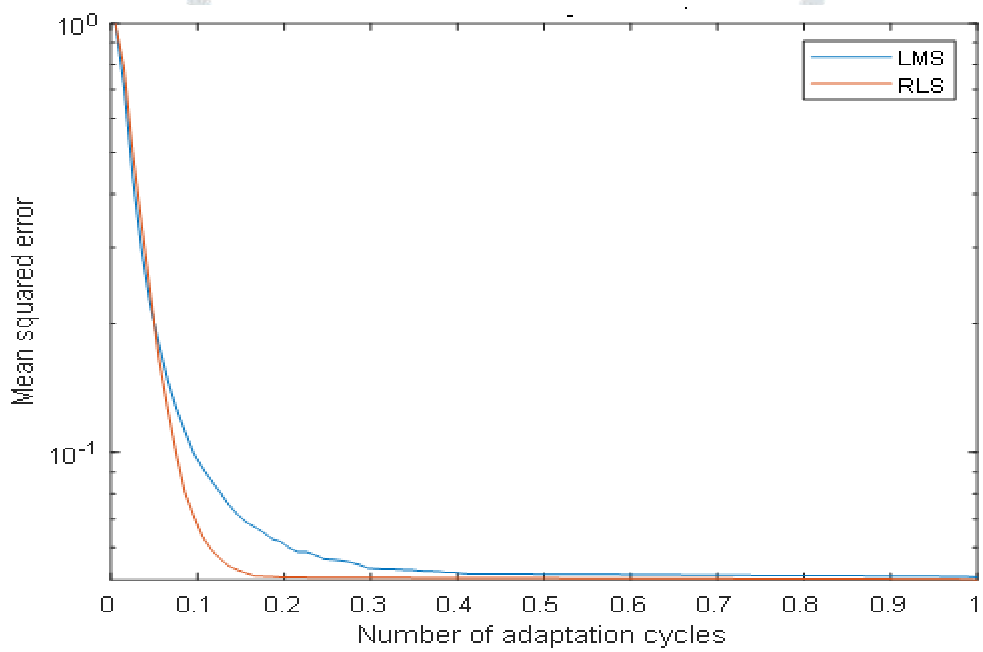

Fig7. MSE of array for N=8

Figures 5 and 6 shows the final weighted array that has a peak at the desired of 00 and a null at the interfering direction 600. The figure shows that LMS AND RLS beamforming algorithm have recovered the target signal while nulling both the interfering signal and noise Figure shows the desired signal arrives at the angle 00 and the interfering signal at 600. The least mean-square algorithm is used to reach the optimum weights as the following results demonstrated. The algorithm also have to go through many iterations before acceptable convergence is achieved, but it is difficult to track the desired signal if the signal changes rapidly.

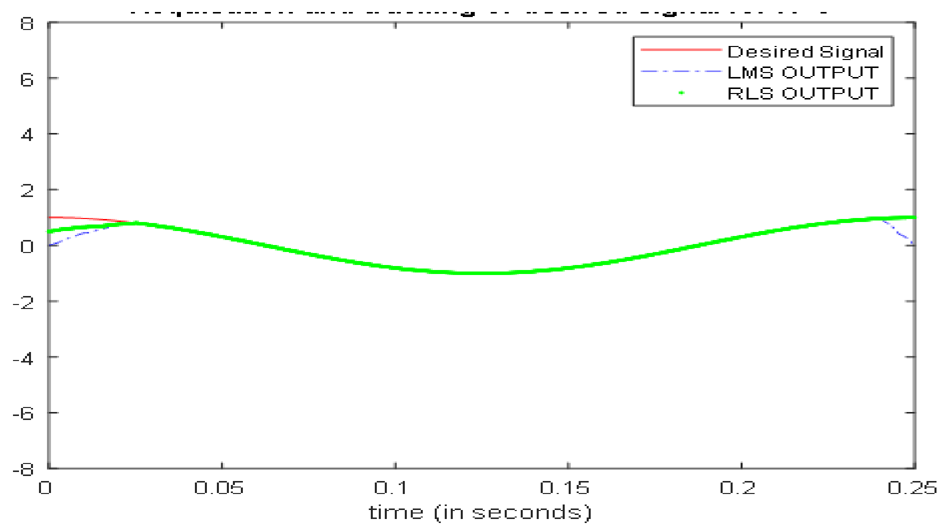

Fig 8. Acquisation and tracking of desired signal for N=8

It is observed from figure 5 that LMS algorithm converges and reaches optimum weights after about 60 iterations. Figures shows the comparison of RLS algorithm and LMS algorithm, simulation result shows that RLS algorithm is more able to closely track array signal as compared to LMS algorithm.

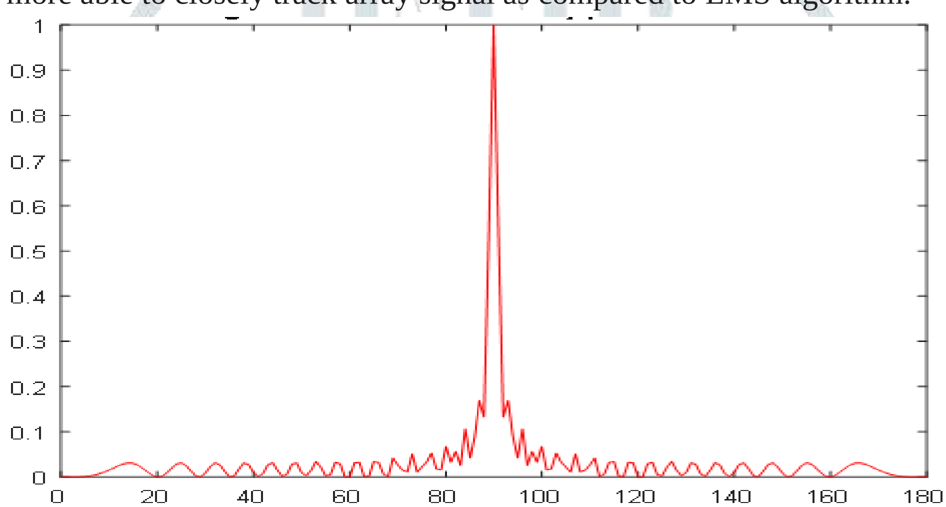

Fig9. Weighted LMS and RLS array pattern for N=32

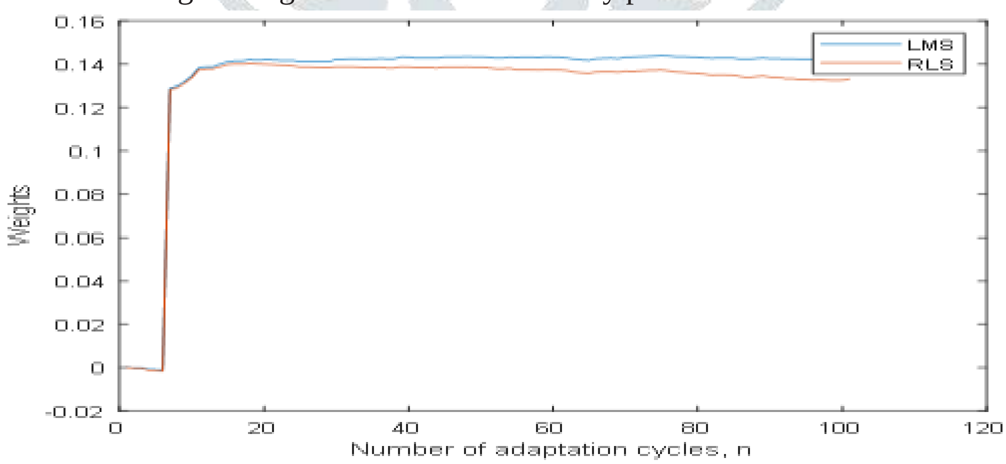

Fig10. Magnitude of array weights for N=32

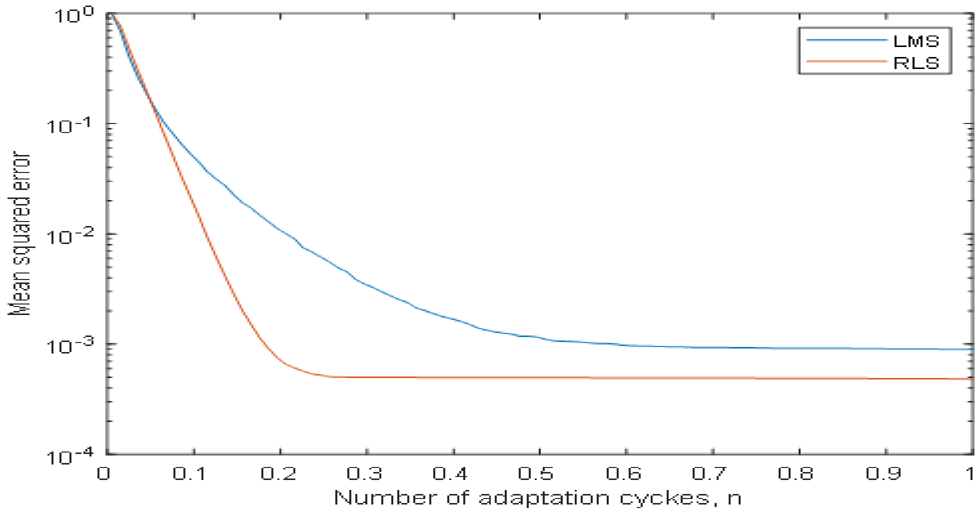

Fig11. MSE of array for N=32

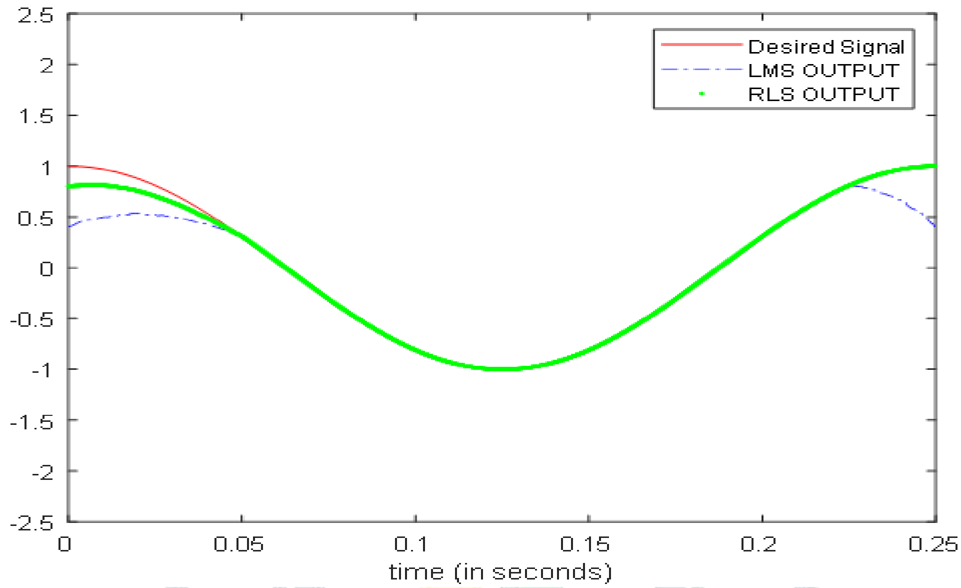

Fig 12. Acquisition and tracking of desired signal for N=32

6. Conclusion

In conclusion, the mm-Wave technology makes a strong case for accommodating the arduous demands of low latency high data rate services for 5G. It is observed that LMS is the simplest and more suitable choice because of its simplicity and a reasonable performance. The results obtained using the proposed RLS algorithm, the resulting mean square error (MSE) that converges to zero after about 60 iterations. The obtained results shows the final weighted array that has a peak at the desired of 0° and a null at the interfering direction is60°. The experimental results also shows that RLS and LMS beamforming algorithm has recovered the target signal while nulling both the interfering signal and noise.

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