A Comparative Analysis of Adaptive 5G Beam-Forming Algorithms

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***Abstract*—Coexisting wireless technologies might impede the performance of the received signal in a 5G network by causing interference. This work suggests a unique method for processing antenna arrays that deals with interference-coexistence communication. We employ a linear filter called the Linearly Constrained Minimum Variance (LCMV) filter. Incorporating it into the conventional single linearly restricted least mean square cost function, we impose a log-sum penalty on the coefficients (LC-LMS). Weights for iterative filters are computed using a formula. We demonstrate that the innovative method's convergence rate is faster than the traditional one using simulations in an antenna environment with an interest signal, noise, and interferences. The recommended approach's mean-square-error (MSE) is also supported. The proposed adaptive beam generating method is applicable to a 5G system to deal with signal and interference coexistence.**

***Index Terms*—Array Factor, Uniform Linear Array, Least Mean Squares, Recursive Least Squares, Conjugate Gradient Method, Linearly Constrained Minimum Variance, Direction of Arrival, Signal of Interest**

INTRODUCTION

The existing long-term evolution (LTE) system will no longer be able to embrace the network demands such as data rates and spectrum needed to solve the challenges such as the excessive interference. Given that, investigations on the performance of the system with respect to the operating frequency and bandwidth such as the Terahertz (THz) bandwidths are already ongoing because of the high capacity figures it provides. On the other hand, higher frequencies are extremely fragile especially in wider distances which enforces the fact that higher frequencies are best for indoor communications. This has encouraged researchers to investigate the possibility of designing transmitters that are able to radiate stronger signals without increasing the power, examples of such techniques are beamforming, and multiple input multiple-output (MIMO). These techniques enable high signal gains and may extend the reach of the signals but it also increases antenna sizes, and the complexity of antenna designs at both transmitters and receivers. This is evidenced by the study which concluded that performance degradation is proportional to antenna size. The study has also highlighted some of the technical challenges that researchers should realize before approaching the technology. While massive MIMO and cell-free technologies are deemed to be some of the exciting innovations for the 5G communication paradigm, beamforming extends the use of such technologies by exploiting the broad range of antenna elements to provide high security, enhanced energy efficiency (EE), good communication reliability, and low signal processing complexity. Cell-free technology is one of the areas that could adopt the beamforming technology to enhance the directivity and connectivity in wireless networks whereby a user is connected to several distributed antennas instead of the conventional systems to insure maximum sum rate reception. Subsequently, interference is considered the most destructive factor to wireless communication systems. Therefore, the availability of proper channel models of the conventional LTE communication system such as Rayleigh, Okumura-Hata etc. has made it easy for researchers to investigate and propose innovative ways to overcome the interference issue. On the other hand, electromagnetic radiations are generally categorised into non-ionising radiations such as infra-red, microwave, radio frequency etc., and ionising radiations such as X-rays. The non-ionising radiations define the ones that have insufficient energy to break the atoms and turn them into ions that is it does not cause any damages to the human body. Whereas the ionising radiations at high doses increase the risks of cancer, birth and DNA defects etc. However, concerns of thermal heating caused by the electromagnetic radiations were raised. Therefore, the FCC limits the maximum exposure to radio frequency energy measured by the specific absorption ratio (SAR) to 1.6 watts per kilogram for mobile phones. The motivation behind the development of the 5G system (i.e. the rapid unprecedented growth of the network, and the increasing network demands) has triggered the researchers to approach the limitations of the fourth generation (4G) communication systems to underlay the new 5G system specifications and services. This network growth can be illustrated in Figure 2 in which the network supports numerous kinds of communications (e.g. agricultural monitoring services, medical services etc.). In such environments, the amount of information exchanged is impressively large which requires advanced technologies to cater for such. The relation between the frequency and the data rate is a major concern whereas low frequencies will not be able to support such demands and high frequencies cannot support wider coverages. Various studies concluded that the traffic is expected to grow to 24.3 Exabytes per month by 2019 on top of the requirements of emerging new services such as cloud computing, smart homes, drone systems, multimedia streaming, point-to-point communication etc. which has now been exceeded already. Therefore, 5G communication system is the revolution of wireless communication in which impressive applications and exceptional data rates and performance are supported. This necessitates fundamental changes in communication infrastructure and innovative realisation of the expected performance.

SYSTEM MODEL

To simplify the optimization issue and assess algorithm performance, uniform linear arrays (ULA) are used. At the receiving end, the narrow band signals appear as plane waves. The arrays are lined up in the model at regular intervals. The angle between DOA and the y axis is known as the angle of incidence. The ULA model is shown as Fig.

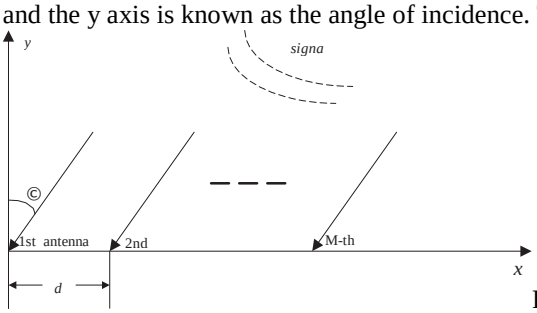

Fig1 ULA

The array has M antennas and can pick up noise, SOI, interferences, and all other types of signals. We assume there are one SOI and m (0<=m<M) interferences. The incident angles of SOI and interferences and are expressed as θ_0 and θ_i (i = 1, …, m) respectively. In the ULA, it is assumed that the distance between two adjacent antennas d is λ/2 (λ is the signal wavelength). Then the phase difference between the two adjacent antennas is πsinθ. We use the first antenna as a reference. When the incident angle is θ_k (k= 0, …, m) the corresponding steer vector can be written as $a(\theta_k) = [1, e^{j\sin\theta k}, \ldots, e^{j\pi(M-1)\sin\theta k}]^{T.}$ Then the whole steer vector is $a = [a(\theta_{0)}, a(\theta_{1),\ldots,}a(\theta_{m)}]$. With n ranging from 1 to N, we use N to signify signal length and x(n) to denote the nth snapshot to create the transmitted signal. Then the whole signal x is expressed as below

$$\begin{aligned} \mathbf{x} &= \left[\mathbf{x}(1), \mathbf{x}(2), \ldots, \mathbf{x}(N)\right] \\ &= \mathbf{a} * \mathbf{S} + \nu \end{aligned}$$

where S is a signal matrix [(m+1) x N] that contains one SOI and m interferences (v) donates the additive white Gaussian noise(AWGN). It is thought to be immune to interference and SOI. In this study, we provide novel LCMV algorithms. The output power is used as the cost function in the LCMV criterion. Frost made the first suggestion. Additionally, it performs well in anti-interference. However, the convergence rate runs counter to steady state. The method has been significantly improved by other academics. To advance it, however, further work is still required. In response to, we provide a novel approach built on the LCMV framework. The cost function is subject to the logsum penalty. Through mathematical derivation, we arrive to the ultimate formulation. Simulations are run to demonstrate the novel method's superiority to the conventional singly linearly constrained LMS. The method outperforms other methods in convergence rate and steady state. Notations: the superscripts $(.)^H$ and $(.)^{-1}$ denote the transpose and inverse operators, respectively. E[.] denotes the expectation operator and sign[.] is the component-wise sign function defined as below

LOG-SUM LC-LMS ALGORITHM

Review of LC-LMC Algorithm

LC-LMS algorithm was proposed to adjust coefficients of the array in real time. Here, we make a short review of the algorithm. Let y(n) be the observed output of antenna array

where $w(n) = [w_1(n), w_2(n), \ldots, w_M(n)]^H$ is the estimated filter coefficient vector, $x(n) = [x_1(n), x_2(n), \ldots, x_M(n)]^H$ is the array input vector. Then the desired output d(n) is expressed as

$$d(n) = \mathbf{w}_o^H(n)\mathbf{x}(n) + N(n)$$

In the above eq sig $\begin{cases} 0, & x = 0 \end{cases}$ efficient vector and N(n) is the observation AWGN with zero mean and variance (σ^2). The LCLMS filter aims to minimize the output power and maintain the response of the SOI. The optimization problem can be written as

$$\min P_{out} = \min E\left[|y(n)|^2\right]$$

where s donates the M nd z is the constraint. The output power can be expressed as

$$E\left[|y(n)|^2\right] = E\left[\mathbf{w}^H(n)\mathbf{x}(n)\mathbf{x}^H(n)\mathbf{w}(n)\right] = \mathbf{w}^H(n)\mathbf{R}\mathbf{w}(n)$$

We use instantaneous covariance R to replace $E[x(n)x^H(n)]$. Then the cost function is defined as

$$L(w) = E\left[|y(n)|^2\right] + \lambda(\mathbf{s}^H\mathbf{w} - z)$$

The steepest des ation of w(n)

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \frac{\mu}{2}\nabla_w L(\mathbf{w})$$

μ is the step factor. On substituting equations, we get

$$\mathbf{w}(n+1) = (\mathbf{I} - \mathbf{H})(\mathbf{I} - \mu\mathbf{R})\mathbf{w}(n) + \mathbf{G}z$$

Where $G = s(s^Hs)^{-1}$ and $H = s(s^Hs)^{-1}s^H$.

To make the algorithm converge to optimal value, should satisfy the condition

$$0 < \mu < \frac{2}{|\lambda_{\max}|}$$

λ is the max eigenvalue of R. In addition, combining and $\Delta_w L = 0$, we can get the optimal solution

Here, modulus value $w_o = \frac{1}{s^H R^{-1} s} R^{-1} s$ show the convergence rate. Steady state is characterized by MSE.

B. The proposed Algorithm

We incorporate a log-sum penalty on the coefficients and add it to the cost function based on conventional, single linearly constrained least mean square (LC-LMS). We arrive at the filter weights' iterative formula through computer simulations of an antenna environment with an interesting signal, noise, and interference. In this section, we provide the new algorithm's precise derivations. On the basis of LC-LMS the recently developed technique penalizes the object function with a log-sum.

"In adaptive filtering applications for modeling, equalization, control, echo cancellation, and beamforming, the widely used least-mean-square (LMS) algorithm has proven to be both a robust and easily-implemented method for on-line estimation of time-varying system parameters. Fig shows a generic adaptive beamforming system which requires a reference signal, the

outputs of the individual sensors are linearly combined after being scaled using corresponding weights such that the antenna array pattern is optimized to have maximum possible gain in the direction of the desired signal and nulls in direction of interferers.

The output of the antenna array is given by,

$$x(t) = s(t)a(\theta_0) + \sum_{i=1}^{N_u} u_i(t)a(\theta_i) + n(t)$$

S(t) denotes the desired signal arriving at angle and $u_i(t)$ denotes interfering signals arriving at angle of incidences respectively. a(θo) and a(θi) represents the steering vectors for the desired signal and interfering signals respectively. Therefore, it is required to construct the desired signal from the received signal amid the interfering signal and additional noise n(t). As shown above the outputs of the individual sensors are linearly combined after being scaled using corresponding weights such that the antenna array pattern is optimized to have maximum possible gain in the direction of the desired signal and nulls in the direction of the interferers. The weights here will be computed using LMS algorithm based on Minimum Squared Error (MSE) criterion. Therefore the spatial filtering problem involves estimation of signal from the received signal (i.e. the array output) by minimizing the error between the reference signal , which closely matches or has some extent of correlation with the desired signal estimate and the beamformer output y(t) (equal to w*x(t)). This is a classical Weiner filtering problem for which the solution can be iteratively found using the LMS algorithm".

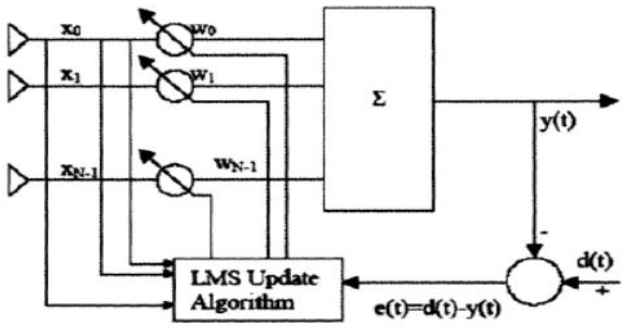

Fig. : LMS adaptive beamforming network

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new sample which is referred to as sample by sample techniques. The algorithm recursively computes and updates the weight vector. This is intuitively reasonable that successive corrections to the weight vector in the direction of the negative of the gradient vector should eventually lead to the MMSE, at which point the weight vector assumes its optimum value.

The LMS algorithm is a member of stochastic gradient algorithms since the instantaneous estimate of the gradient vector is a random vector that depends on the input vector x(n). The rate of convergence is slow for a small value of μ but this gives a good estimation of the gradient vector since a large amount of data is taken into account. The algorithm requires knowledge of the transmitted signal. This is accomplished by periodically sending some known pilot sequences that are known to the receiver. As stated above, step size μ is a positive real-valued constant which controls the size of the incremental correction applied to the weight vector as we proceed from one iteration cycle to the next. The performance of the algorithm depends on the step size parameter, which controls the convergence speed and the variation of the learning curve. LMS algorithm uses the Method of Steepest-Descent to update the weight vector. The response of the LMS algorithm is determined by three principal factors: step-size parameter, number of weights, and Eigenvalue of the correlation matrix of the input data vector. Conventionally the LMS adaptive algorithm has been used to update the combining weights of adaptive antenna arrays.
The LMS algorithm initiated with some arbitrary value for the weight vector is seen to converge and stay stable for $0 < \mu < 1/\lambda max$ Where λmax is the largest eigenvalue of the correlation matrix R. The convergence of the algorithm is inversely proportional to the eigenvalue spread of the correlation matrix R. When the eigenvalues of R are widespread, convergence may be slow. The eigenvalue spread of the correlation matrix is estimated by computing the ratio of the largest eigenvalue to the smallest eigenvalue of the matrix. If μ is chosen to be very small, then the algorithm converges very slowly. A large value of μ may lead" to a faster convergence but may be "less stable around the minimum value. One of the literatures [will provide reference number here] also provides an upper bound for μ based on several approximations as $\mu <= 1/(3trace(R))$.

SIMULATION AND RESULTS

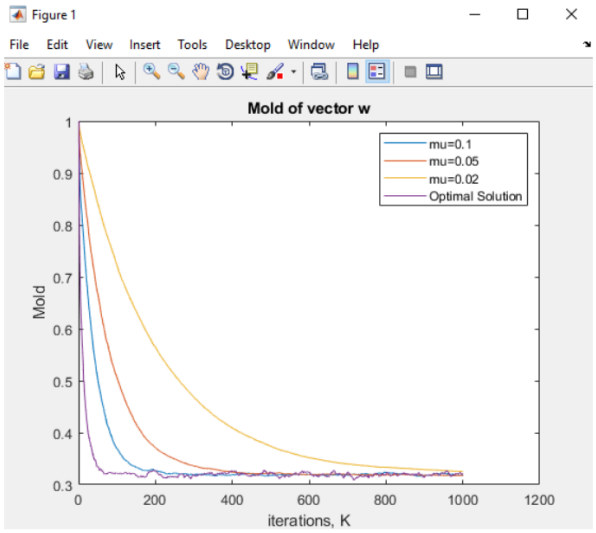
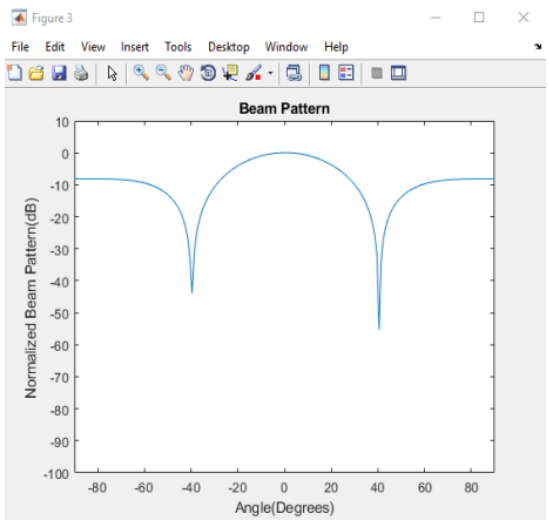


Figure: Convergence Rate with different mu



2. In the second experiment, we analyze the factors that may affect the performance of the method & determine that log-sum LC-LMS has better performance than LCLMS & traditional algorithms — fast convergence rate, lower MSE

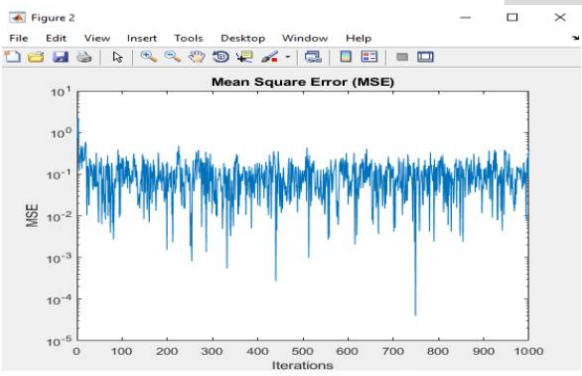


Figure: Mean Square Error with M=4

3. Using the novel adaptive beamforming algorithm, we thus obtain a flat, undistorted & least-interference infected beam pattern, with symmetric null points at +40/-40 degree & peak/major lobe at 0 degree.

4. The adaptive beamformer significantly improves the SNR of the rectangular pulse at t=0.2s (time chosen) (60% AVG noise & interference reduction)

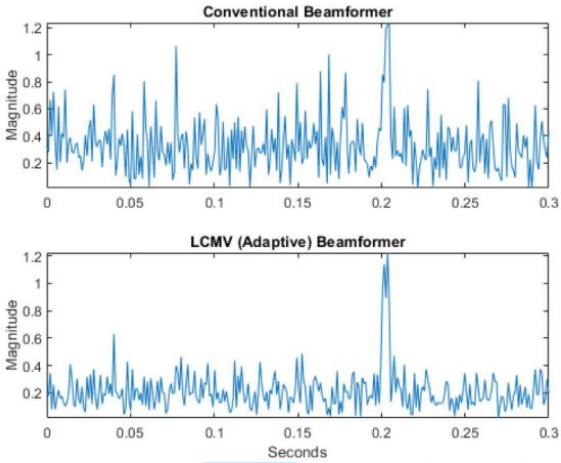


Figure: Signal-to-Noise Ratio

5. The adaptive beam-form places a null at the arrival angle of the interference signal, 120° (50% improvement by null placement)

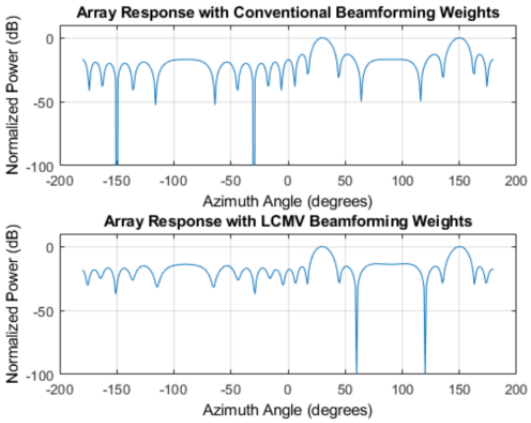


Figure: Normalized Power and Null Point

6. Array factor analysis for 2 predominant blind/non-blind beamforming algorithms — LMS & RLS frameworks.

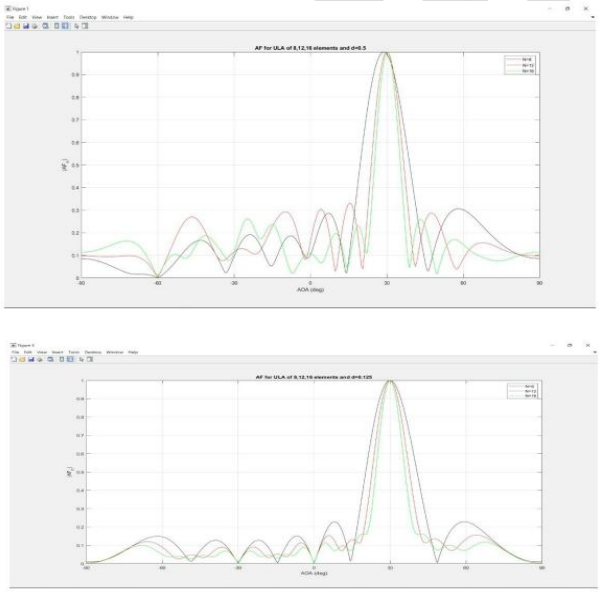


Figure: Array Factor Analysis

CONCLUSION

We proposed a new algorithm based on the LC-LMS. The object function is given a log-sum penalty, and theoretical analysis is

provided step by step until the final formula is derived. After then, experiments are run on the MATLAB platform. The first experiment compares the steady state and convergence rates of the newly suggested method and the LC LMS. The outcomes demonstrate the new method's superiority and efficacy. In the second experiment, we examine the variables that could impact how well the method works. As can be seen, the setting of the parameter t affects how well the algorithm performs. In order to conclude, we compare beam patterns. The log-sum LC-LMS performs as well as or better than the LC-LMS.

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