An improved Adaptive BeamForming Algorithm for 5G Interference-coexistence communication

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***Abstract*—Coexistence of multiple wireless systems in a 5G network can cause interference in the same frequency band and deteriorate the performance of the received signal. In this paper, a novel algorithm is proposed in antenna array processing to handle interference-coexistence communication. We adopt a linear filter which is called Linearly Constrained Minimum Variance (LCMV) filter. On the basis of traditional singly linearly constrained least mean square (LC-LMS), we introduce a log-sum penalty on the coefficients and add it into the cost function. We derive the iterative formula of filter weights. By simulations in antenna environment with signal of interest, noise and interferences, we prove that the convergence rate of the new method is faster than traditional one. Moreover, the mean-square-error(MSE) of the proposed method is also verified. Experiment results demonstrate that our method has lower MSE than the traditional LC-LMS algorithm. The proposed adaptive beamforming scheme can be applied in 5G system to deal with the coexistence of signals and interferences.**

***Index Terms*—Interference-coexistence, LC-LMS, Log-Sum Penalty.**

I. INTRODUCTION

THE deployment and commercial operation of 5G systems are speeding up to meet the anticipated demands of next decade in data transmission. 5G networks are emerging intelligent systems which involve the application of advanced signal processing [1], D2D [2], internet of things (IOT), edge computing [3], and wireless access technologies [4] that have drawn much attention in recent years. In a 5G network, coexistence of multiple wireless systems can cause interference in the same frequency band and deteriorate the received signal. The anti-interference communication will still play an important role in the network. The adaptive beamforming technology has always been an import part in antenna processing to handle interference problem. The direction information is added into the transmitted signal with the technology and then the mixed signal, including signal of interest(SOI), interferences and noise, is received at receive end. Actually, SOI have different Direction of Arrival(DOA) compared with interferences. Adaptive algorithms ensure to produce null points towards the directions of interferences while maintain the gain of SOI.

The earliest least-mean-square(LMS) algorithm is proposed by Widrow and Hoff [5]. It is popular for its simplicity and received worldwide interest. But the convergence rate and steady state error are not as much satisfying. The derivations of LMS have fixed the problems to a certain extent. The adjustment of LMS is directly proportional to the input vector, so when the input is very large, the algorithm suffers from a gradient noise amplification problem. Normalized LMS algorithm [6] takes the squared Euclidean norm of the input vector at each adaptation and has well solved the problem. Also, variable-step LMS [7] [8] have improved the convergence rate a lot. All these above mentioned derivations minimize the mean-square-error(MSE) between the estimation signal and the desired one. The criterion used in derivation is Minimum-Mean-Square-Error(MMSE) which takes MSE as cost function. It is noted that no constraints have been added to the solution. In [9], based on LMS in MMSE, the author introduce two different penalties on the cost function. Results show that the algorithm with penalty outperforms LC-LMS in convergence.

In this paper, we propose a new algorithms in LCMV. LCMV criterion takes the output power as cost function. It was first proposed by Frost[10]. And it works well in anti-interference. But the convergence rate contradicts with steady state. Many researchers have done a lot to improve the algorithm. However, there still needs more works to push it further. On this point, motivated by [9], we propose a new method on the basis of LCMV. Log-sum penalty is imposed on the cost function. We get the final formulation through mathematical derivation. Compared with traditional singly linearly constrained LMS, simulations are carried out to prove the new method's superiority. The method outperforms other methods in convergence rate and steady state.

$Notations$: In the following parts, the superscripts $(\cdot)^H$ and $(\cdot)^{-1}$ denote the transpose and inverse operators, respectively. $E[\cdot]$ denotes the expectation operator and sign$[\cdot]$ is the component-wise sign function defined as below

$$\text{sign}\left[x\right] = \begin{cases} x/\left|x\right|, & x \neq 0 \\ 0, & x = 0 \end{cases} \tag{1}$$

II. SYSTEM MODEL

Uniform linear array(ULA) is used to simplify the optimization problem and analyze algorithm performance. The signals are narrow band and can be seen as plane wave at receive end. In the model, the arrays are arranged in a line with equal intervals. The angle of incidence θ is the angle between DOA and y axis. The ULA model is shown as Fig. 1.

This work is supported by "the Fundamental Research Funds for the Central Universities (2019PTB-017)".

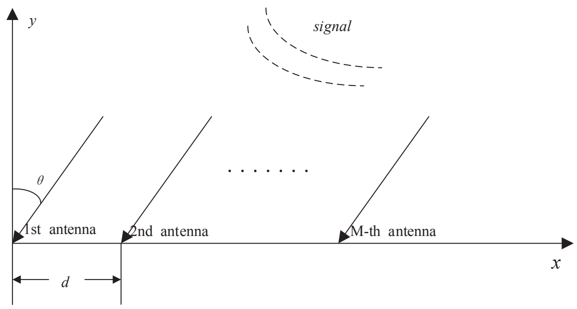

Fig. 1: ULA

The array consists of M antennas and is used to receive signals, including SOI, interferences and noise. We assume there are one SOI and m $(0 \leq m < M)$ interferences. The incident angles of SOI and interferences are expressed as θ_0 and $\theta_i (i = 1, ..., m)$, respectively.

In the ULA, it is assumed that the distance between two adjacent antennas d is $\lambda/2$ (λ is the signal wavelength). Then the phase difference between the two adjacent antennas is $\pi \mathrm{sin}\theta$. 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 $\mathbf{a}(\theta_k) = \Big[1, e^{j\pi \mathrm{sin}\theta_{\mathrm{k}}}, ..., e^{j\pi(M-1)\mathrm{sin}\theta_{\mathrm{k}}}\Big]^T$. Then the whole steer vector is $\mathbf{a} = \Big[\mathbf{a}(\theta_0), \mathbf{a}(\theta_1), ..., \mathbf{a}(\theta_m)\Big]$.

In order to construct transmitted signal, we use N denote signal length and $\mathbf{x}(n)$ denote the n-th snapshot with n ranges from 1 to N. Then the whole signal $\mathbf{x}$ is expressed as below

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

where $\mathbf{S}$ is a $\Big[(m+1) \times N\Big]$ signal matrix that contains one SOI and m interferences. ν donates the additive white gaussian noise(AWGN). It is assumed to be independent from SOI and interferences.

III. Log-sum LC-LMS Algorithm

A. Review of LC-LMS Algorithm

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

$$y(n) = \mathbf{w}^H(n)\mathbf{x}(n) \tag{3}$$

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

$$d(n) = \mathbf{w}_o^H(n)\mathbf{x}(n) + N(n) \tag{4}$$

In the above equation, $\mathbf{w}_o$ is the optimal coefficient vector and $N(n)$ is the observation AWGN with zero mean and σ^2 variance. The LC-LMS filter aims to minimize the output power and maintain the response of the SOI. The optimization problem can be written as

$$\begin{aligned} &\min P_{out} = \min E\Big[|y(n)|^2\Big] \\ &\text{s.t.} \quad \mathbf{s}^{\mathrm{H}}\mathbf{w} = \mathrm{z} \end{aligned} \tag{5}$$

where $\mathbf{s}$ donates the $M \times 1$ steer vector of SOI and z is the constraint. The output power can be expressed as

$$E\Big[|y(n)|^2\Big] = E\Big[\mathbf{w}^H(n)\mathbf{x}(n)\mathbf{x}^H(n)\mathbf{w}(n)\Big] = \mathbf{w}^H(n)\mathbf{R}\mathbf{w}(n) \tag{6}$$

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

$$L(w) = E\Big[|y(n)|^2\Big] + \lambda(\mathbf{s}^H\mathbf{w} - z) \tag{7}$$

The steepest descend method is used to get the solution of $\mathbf{w}(n)$

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \frac{\mu}{2}\nabla_w L(\mathbf{w}) \tag{8}$$

In equation (8), μ is the step factor. By substituting (7) into (8), iteration expression of (8) can be rewritten as

$$\mathbf{w}(n+1) = (\mathbf{I} - \mathbf{H})(\mathbf{I} - \mu\mathbf{R})\mathbf{w}(n) + \mathbf{G}z \tag{9}$$

where $\mathbf{G} = \mathbf{s}(\mathbf{s}^H\mathbf{s})^{-1}$ and $\mathbf{H} = \mathbf{s}(\mathbf{s}^H\mathbf{s})^{-1}\mathbf{s}^H$.
To make the algorithm converge to optimal value, μ should satisfy the condition [13]

$$0 < \mu < \frac{2}{|\lambda_{\max}|} \tag{10}$$

$\lambda_{\max}$ is the max eigenvalue of $\mathbf{R}$. In addition, combining equation (7) and $\nabla_w L = 0$, we can get the optimal solution

$$\mathbf{w}_o = \frac{1}{\mathbf{s}^H\mathbf{R}^{-1}\mathbf{s}}\mathbf{R}^{-1}\mathbf{s} \tag{11}$$

B. The proposed Algorithm

In this part, we give the specific derivations of the new algorithm. The newly proposed algorithm adds log-sum penalty to the object function on the basis of LC-LMS. The optimization problem is expressed as follows

$$\begin{aligned} &\min P_{out} = \min E\Big[|y(n)|^2\Big] \\ &\text{s.t.} \begin{cases} \mathbf{s}^H\mathbf{w} = z \\ \sum\limits_{i=1}^{M} \log(1 + \mid w_i \mid /\varepsilon') = t \end{cases} \end{aligned} \tag{12}$$

w_i is the i-th element of the vector $\mathbf{w}(n)$. ε' is a parameter that determines how much each element contributes to the penalty t. Then the Lagrange function can be written as

$$\begin{aligned} L(w) =& E\Big[|y(n)|^2\Big] + \lambda_1(\mathbf{s}^H\mathbf{w} - z) \\ &+ \lambda_2\left[\sum_{i=1}^{M}\log(1 + \mid w_i \mid /\varepsilon') - t\right] \end{aligned} \tag{13}$$

Similarly, through steepest descend method, we get

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \frac{\mu}{2}\Big\{2\mathbf{R}\mathbf{w}(n) + \mathbf{s}\lambda_1 + \lambda_2\mathbf{B}\Big\} \tag{14}$$

where $\mathbf{B} = \frac{\varepsilon \text{sign}[\mathbf{w}(n)]}{1+\varepsilon|\mathbf{w}(n)|}$ and $\varepsilon = \frac{1}{\varepsilon'}$. Pre-multiplying equation (14) with $\mathbf{s}^H$ and using the constraint $\mathbf{s}^H\mathbf{w}(n+1) = z$, λ_1 is

$$\lambda_1 = \frac{2}{\mu}\mathbf{H}\mathbf{w}(n) - \frac{2}{\mu}\mathbf{G}z - 2\mathbf{H}\mathbf{R}\mathbf{w}(n) - \lambda_2\mathbf{B} \tag{15}$$

where $\mathbf{G} = (\mathbf{s}^H\mathbf{s})^{-1}$ and $\mathbf{H} = (\mathbf{s}^H\mathbf{s})^{-1}\mathbf{s}^H$.
In order to reduce the complexity, we make an approximation

$$\text{sign}^H\Big[\mathbf{w}(n)\Big]\mathbf{w}(n+1) \approx t \tag{16}$$

The approximation is on the basis of $\mathbf{w}(n+1) \approx \mathbf{w}(n)$ when n is large enough. Now we define $t_n = \text{sign}^H\Big[\mathbf{w}(n)\Big]\mathbf{w}(n)$ and make another approximation

$$\text{sign}^H\Big[\mathbf{w}(n)\Big]\text{sign}\Big[\mathbf{w}(n)\Big] \approx M \tag{17}$$

Then pre-multiply equation (14) with $\text{sign}^H[\mathbf{w}(n)]$ and eliminate $\mathbf{w}(n+1)$

$$\begin{aligned} t =& t_n - \frac{\mu}{2}\Big\{2\mathbf{w}(n)\mathbf{R}\mathbf{w}(n) + \text{sign}^H\big[\mathbf{w}(n)\big]\mathbf{s}\lambda_1 \\ &+ \lambda_2 T \text{sign}^H\big[\mathbf{w}(n)\big]\text{sign}\big[\mathbf{w}(n)\big]\Big\} \end{aligned} \tag{18}$$

where $T = \frac{\varepsilon}{1+\varepsilon|\mathbf{w}(n)|}$. λ_2 can be denoted as

$$\begin{aligned} \lambda_2 =& \Big(-\frac{2}{TM\mu}\Big)e_L(n) - \frac{2}{TM}\text{sign}^H\big[\mathbf{w}(n)\big]\mathbf{R}\mathbf{w}(n) \\ &- \frac{1}{TM}\text{sign}^H\big[\mathbf{w}(n)\big]\mathbf{s}\lambda_1 \end{aligned} \tag{19}$$

where $e_L(n) = t - t_n$. Through (15) and (19), we can obtain the solutions of λ_1 and λ_2. Finally, (14) can be rewritten as

$$\begin{aligned} \mathbf{w}(n+1) =& \mathbf{P}\Bigg\{\mathbf{I} + \frac{\text{sign}\big[\mathbf{w}(n)\big]\text{sign}^H\big[\mathbf{w}(n)\big]\mathbf{s}\mathbf{H}}{MQ(n)}\Bigg\}\mathbf{w}(n) \\ &- \mathbf{P}\Bigg\{\mathbf{I} - \frac{\text{sign}[\mathbf{w}(n)]\text{sign}^H\big[\mathbf{w}(n)\big]}{MQ(n)}\mathbf{P}\Bigg\}\mu\mathbf{R}\mathbf{w}(n) \\ &+ \mathbf{P}\frac{\text{sign}[\mathbf{w}(n)]}{MQ(n)}e_L(n) \end{aligned} \tag{20}$$

where

$$\mathbf{P} = \mathbf{I} - \mathbf{s}\mathbf{H}$$
$$Q(n) = 1 - \frac{1}{TM}\text{sign}^H[\mathbf{w}(n)]\mathbf{s}\mathbf{H}\mathbf{B}$$

IV. Simulation and Results

In this section, the performance of the new algorithm is compared with tradition method on Matlab platform. Several experiments have been done to prove the new method's performance in convergence rate and steady state. Here, we use modulus value of coefficient $\mathbf{w}(n)$ to show the convergence rate. Steady state is characterized by MSE. Each experiment is ran many times independently. The specific parameters used in the following experiments are described in Table.I.

In the first experiment, we compare the new algorithm with LC-LMS in convergence rate and steady state. First, we use four antennas with one SOI and one interference. The parameters z, t and ε' are set to be 1.0, 1.0 and 10, respectively. We set the initial value of the weights vector $\mathbf{w} = [1, 0, 0, 0]^H$. The optimal coefficient $\mathbf{w}_o$ is also provided in the figure. Then the antenna number increases but the transmitted signal remains the same as before. We test how antenna number affect the result. Finally, we set $M = 16$, increase interference number, keep other parameters unchanged and do similar test.

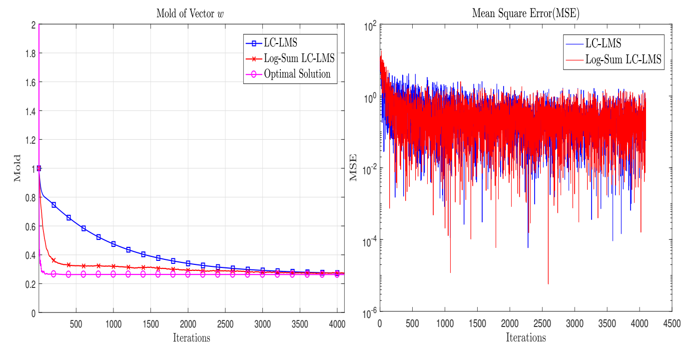

Fig. 2: convergence rate and MSE with $\mu = 5 \times 10^{-4}$ and $M = 4$

From Fig.2, we can see that LC-LMS slowly converges to optimal value at $n = 3500$ while the new method converges at $n = 2500$. The new method has faster convergence and relatively lower MSE than LC-LMS. In addition, we can note that log-sum LC-LMS quickly converges to the optimal value at the beginning and then slowly approaches the value.

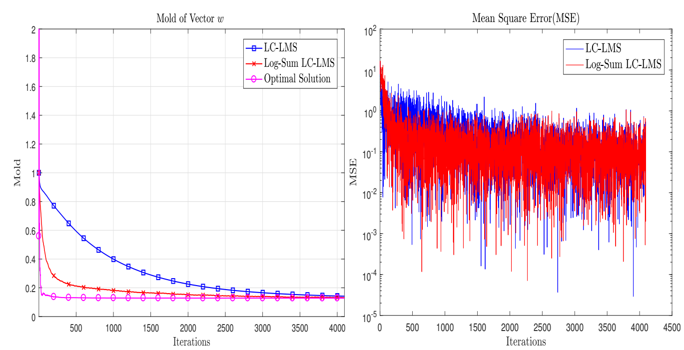

Fig. 3: convergence rate and MSE with $\mu = 5 \times 10^{-4}$ *and* $M = 8$

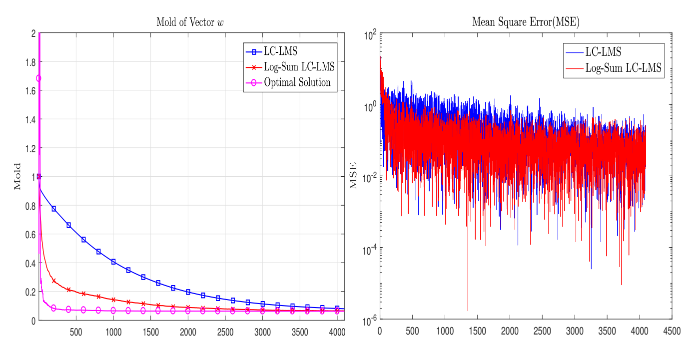

Fig. 4: convergence rate and MSE with $\mu = 5 \times 10^{-4}$ *and* $M = 16$

From Fig.3 and Fig.4, LC-LMS converges at $n = 3500$ and the new method converges at $n = 2500$, which has not

TABLE I: Parameter Specification

Term		Value							
M		4	8	16					
JAM	number	1		1	2		3		
	angle/degree	40		40	-30	40	-30	40	70
SOI	number	1							
	angle/degree	0							
SIR/dB		-20							
N		4096							
t		1.0							
z		1.0							
ε'		10							
μ		5×10^{-4}							

much differences from before. But as the antenna number increases, the steady state of the new method becomes more evident. It has lower MSE when iteration begins and reaches the steady MSE state faster compared with LC-LMS.

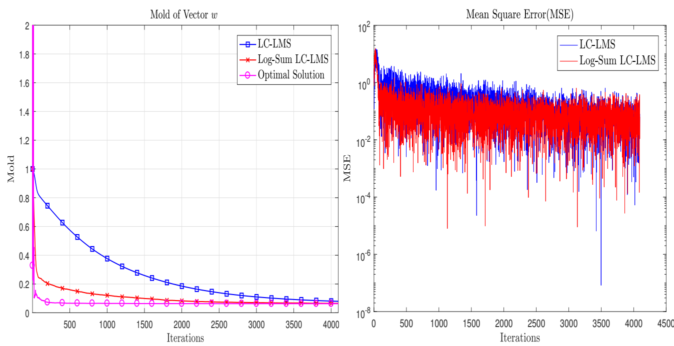

Fig. 5: convergence rate and MSE with $\mu = 5 \times 10^{-4}$, $M = 16$ and two Interferences

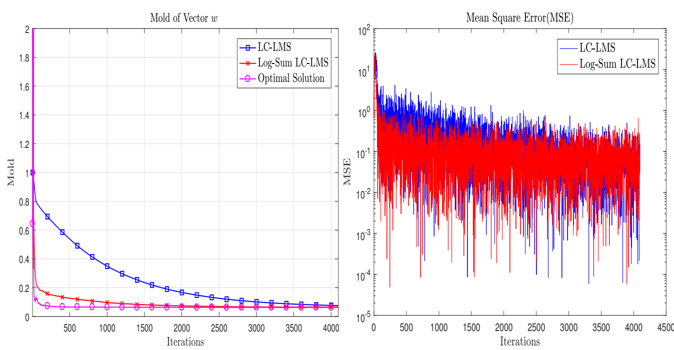

Fig. 6: convergence rate and MSE with $\mu = 5 \times 10^{-4}$, $M = 16$ and three Interferences

From Fig.5 and Fig.6, we can see that when interferences increase, the new method still works better than LC-LMS.

In the second experiment, we analyze how the parameters affect the new algorithm. We choose different ε', t and μ. In one scenario, we set $M = 8$ and $N = 10240$ with one SOI and one interference as shown in Table.I. We use constant value $\varepsilon' = 10$ and $t = 1.0$. The μ values are different. The result is shown in Fig.7. In the figure, we can get the conclusion that larger μ will accelerate the convergence rate when μ is in reasonable range.

In another scenario, we use constant value $\mu = 5 \times 10^{-4}$

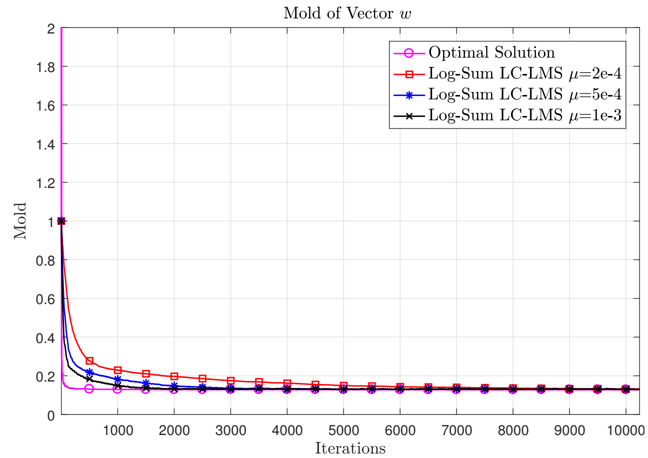

Fig. 7: convergence rate with different μ.

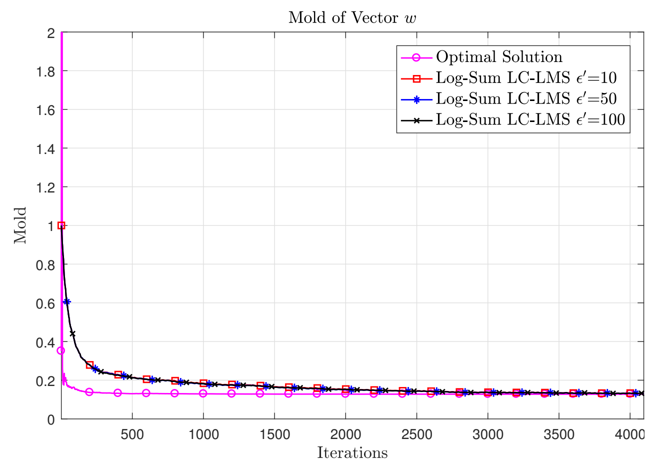

Fig. 8: convergence rate with different ε'.

and $t = 1.0$. Here, N is set to be 4096. The ε' values are different while other parameters are same as before. In Fig.8, the ε' values have little effect on the convergence. It is easy to understand the result from the original penalty condition.

$$\sum_{i=1}^{M} \log(1 + \frac{|w_i|}{\varepsilon'}) = t \tag{21}$$

In the equation (21), ε' and t together make effect on w. ε' is only a parameter that determines how much each element of $\mathbf{w}$ contributes to the penalty and is placed in log function, while t determines the penalty added to the object function. So what makes a difference to the result is the parameter t. Then we give an analysis on t.

In Fig.9, $\mu = 5 \times 10^{-4}$ and $\varepsilon' = 10$. Other parameters are set unchanged. We can note that when t is too big, the coefficient vector $\mathbf{w}$ could not converge to optimal value. However, when t is too small, the result will be sharply jittered around the optimal value. It is vital that we choose proper value for t, or the algorithm will deteriorate seriously.

Finally, we take a look at beam pattern of the algorithm. Beam pattern is defined as below

$$F(\theta) = |\mathbf{w}^H \mathbf{a}(\theta)| \tag{22}$$

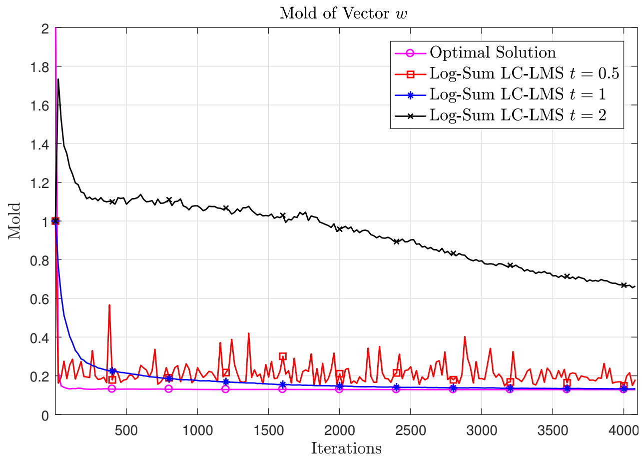

Fig. 9: convergence rate with different t

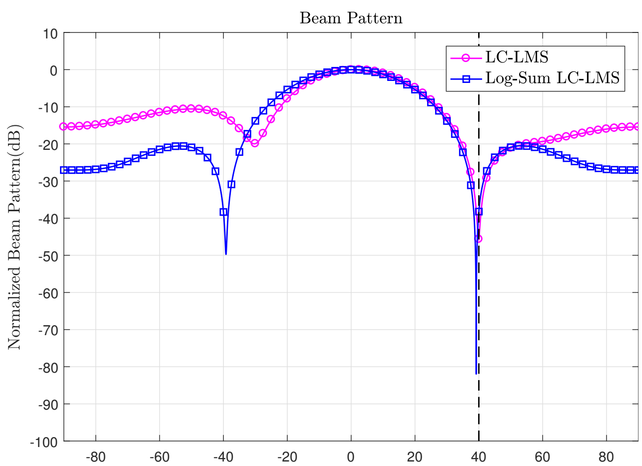

Fig. 10: Beam Pattern $M = 4$ with one interference

Usually, we use normalized $F(\theta)$ as a reference

$$G(\theta) = 20\log_{10}\left\{\frac{F(\theta)}{\max\left[F(\theta)\right]}\right\} \tag{23}$$

Here, The parameters we used are shown in Table.I.

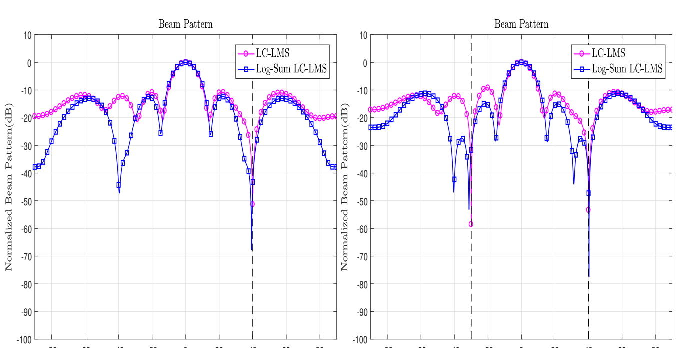

Fig. 11: Beam Pattern $M = 8$ with different interferences

In Fig.10, the interference is at 40 degrees and SOI at 0 degree. The pattern gets max gain at 0 degree and produces deep null point at 40 degrees. By comparison, the two algorithms both get similar gain at SOI incident degree. But Log-sum LC-LMS has deeper null point than LC-LMS and the gain is about 35dB lower.

In Fig.11, the left figure is the beam pattern with one interference while the right with two. The incident angle of interference of the left is 40 degrees, while the right are -30 and 40 degrees. They both produce deep null point at interference angles and get max gain at SOI angle. In the right figure, when incident angle of interference is 40 degrees, the null point gain of Log-sum LC-LMS is about -75dB which is lower than -55dB of LC-LMS. When the angle is -30 degrees, the gain of Log-sum LC-LMS is about 5dB higher than LC-LMS. So the new algorithm is not always superior to LC-LMS in beam pattern. But in general, log-sum LC-LMS is comparable to LC-LMS or better.

V. Conclusion

In this paper, we propose a new algorithm based on the LC-LMS. We add log-sum penalty to the object function and give theoretical analysis step by step until derive the final formula. Then experiments are carried out on Matlab platform.

The first experiment aims to compare the newly proposed algorithm with LC-LMS in convergence rate and steady state. The results prove the effectiveness and superiority of the new method. In the second experiment, we analyze the factors that may affect the performance of the method. We can see that the choice of parameter t determines the algorithm performance, so t should be set properly. Finally, we make a comparison in beam pattern. The log-sum LC-LMS has the same performance as LC-LMS, or better.

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