USING HIERARCHICAL CODEBOOK AT THE RECEIVER TO IMPROVE THE CHANNEL CAPACITY IN MM WAVE COMMUNICATION

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Ngày nhận bài: 30/03/2021, Ngày chấp nhận đăng: 12/06/2021, Phản biện: TS. Dương Thị Thanh Tú

Abstract:

Mm-wave is currently of interest due to its ability to enhance large bandwidth, which can fully meet the speed of 5G information systems. The beamforming techniques are studied for this wave such as beam weights updating at the receiver to ensure the fastest convergence rate of the weighting algorithm. We need to specify algorithms such as mean least squares (LMS), recursive least squares (RLS), sampling matrix inverse (SMI), conjugate gradient methods (CGM). There are many articles related to the comparison of these algorithms on convergence weighting speed, transmission capacity. However, finding a matrix of receive beams in a multi-path environment is a problem of little interest. Using the hierarchical codebook (HC) is applied to produce suitable gain-weight vectors and requires fewer iterative steps to find beam weights. In addition, compared with the traditional methods mentioned above, such as LMS, RLS, SMI, or CGM, the method of finding beam weights using HC also ensures the increased channel capacity, especially with the high signal-to-noise ratios.
Mm wave communication, beamforming, LMS, RLS, SMI, CGM algorithms, HC, channel capacity.

Keywords:

Truyền thông sóng mm, beamforming, thuật toán LMS, RLS, SMI, CGM, HC, dung lượng kênh truyền.

Tóm tắt:

Sóng mm hiện đang được quan tâm do khả năng tăng cường được băng thông lớn, hoàn toàn có thể đáp ứng được tốc độ cho hệ thống thông tin 5G. Các kỹ thuật beamforming được nghiên cứu cho sóng này như cập nhật trọng số bức xạ tại máy thu với mục đích đảm bảo tốc độ hội tụ thuật toán tìm trọng số là nhanh nhất. Chúng ta cần chỉ rõ các thuật toán như bình phương trung bình nhỏ nhất (LMS), bình phương nhỏ nhất đệ quy (RLS), nghịch đảo ma trận lấy mẫu (SMI), phương pháp đạo hàm liên hợp (CGM). Có nhiều bài liên quan tới việc so sánh các thuật toán này về tốc độ tìm trọng số hội tụ, dung lượng truyền. Tuy nhiên việc tìm một ma trận bức xạ thu trong môi trường đa đường là bài toán ít được quan tâm. Giải pháp sử dụng bộ mã phân cấp (HC) được áp dụng để đưa ra các véc tơ trọng số thu phù hợp và đòi hỏi số bước lặp tìm trọng số bức xạ không cao. Ngoài ra so với các phương pháp truyền thống kể trên như LMS, RLS, SMI hay CGM thì phương pháp tìm trọng số bức xạ sử dụng HC còn đảm bảo được dung lượng kênh truyền tăng cao, đặc biệt với những tỷ số tín hiệu trên nhiễu SNR cao.

1. INTRODUCTION

The current mm-wave is of great interest when its frequency range is from 30 GHz to 300 GHz, ultimately meeting the channel capacity of the 5G system. Although it is affected by propagation conditions a lot, it is an advantage when we can deploy multiple antenna elements at the transmitter and receiver because the antenna size is inversely proportional to the frequency. This opportunity opens the door to exciting antenna techniques such as beamforming or spatial multiplexing. The adaptive beamforming is requested for the 5G communication system. Adaptive beamformer performs spatial signal processing compatibly, which consists of an array of transmitting and receiving antennas [1-2].

Popular adaptive beamforming methods include LMS, RLS, SMI, and CGM. Among them, the LMS beamforming method is relatively simple and has been implemented in many radio communication applications [2].

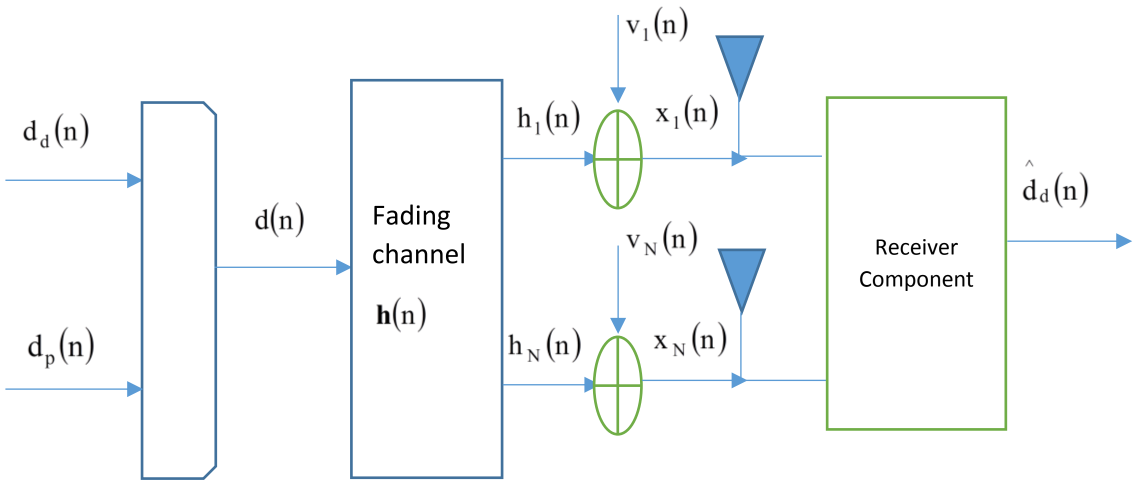

Figure 1. Transceiver architecture

This method can perform beamforming that does not require matrix inversion as used in the SMI method. It uses a fixed step size for beamforming. It makes LMS stable and simple. Therefore this method is often used for many different applications. However, LMS has the slowest convergence rate among the methods mentioned above [1].

One method used to compensate for the Doppler effect is to combine the antenna array at the receiver [3]. It improves beam weights changes over time can be updated using RLS algorithm. Although RLS is more complex than LMS, it can converge more quickly. It even converges faster than SMI [1-2]. The RLS offers an MSE that is smaller than the LMS and Normalised LMS (NLMS) methods, guaranteed within the allowable threshold, while SMI has the lowest MSE [1], [4-7]. In terms of complexity, RLS has better temporal complexity but less spatial complexity than SMI [8-10]. However, the complexity depends on the algorithms' coding, and SMI is optimized for spatial complexity. For a small number of antenna elements, the SMI algorithm has better quality in space, time and MSE than RLS. However, the NLMS, LMS methods are all steepest descent gradient-based iterative algorithms, while SMI and RLS are recursive and block compatible methods, respectively. These methods do not have as high a convergence capacity as CGM because it is difficult to determine the vector's value by eigenvalue when it is spread.

CGM allows convergence even faster than the above methods where it uses perpendicular search while the other methods use eigenvalues with a large spread.

One method used for multipath environments is to use the hierarchical codebook [11]. It shows better energy efficiency and beam weights search capabilities than traditional methods like the exhausitive search. In this article, the author introduces the beam weights search algorithm using hierarchical codebook and proves the ability to converge fast, increase capacity compared to the LMS, RLS, CGM and SMI methods through simulation.

2. CURRENT METHODS FOR FINDING BEAM WEIGHTS

With the channel model used for mm waves, we see that the received signal is generalized as follows:

$$\mathbf{x} = \mathbf{W}^H\mathbf{HFd} + n \tag{1}$$

Where $\mathbf{d}$ is the transmit signal vector, $\mathbf{W}$ is the received beam matrix, $\mathbf{F}$ is the transmitted beam matrix, $\mathbf{H}$ is the channel matrix.

The paper presents two figures to simplify the description of algorithms. Figure 1 depicts the structure of a channel model with the one transmit antenna and the N receive antennas. Figure 2 describes a receiver scheme using a received beam vector.

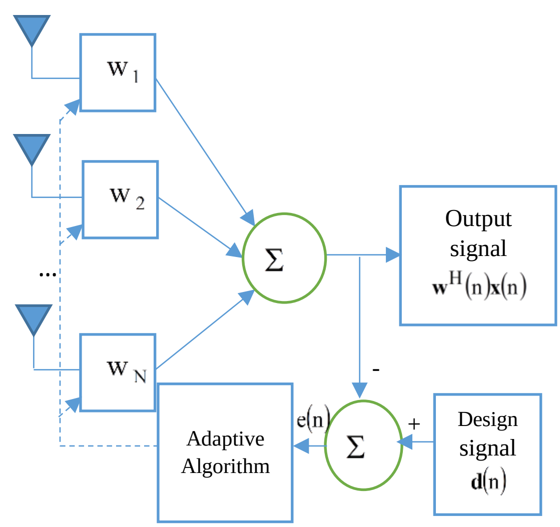

Figure 2. Current beam weight finding methods

LMS Algorithm [2-3]:

$$\mathbf{w}(0) = \mathbf{0}$$

For n=0, 1, 2,…

$$\mathbf{w}(n+1)=\mathbf{w}(n)-\mu\mathbf{e}^{*}(n)\mathbf{x}(n) \quad (2)$$

where

$\mathbf{e}(n)=d(n)-\mathbf{w}^{*}(n)\mathbf{x}(n)$ is error vector

$\mu=\dfrac{2}{3tr(\mathbf{R}_{xx})}$ is step size

SMI Algorithm [2]:

$$\mathbf{R}_{xx}(n)=\frac{1}{k}\sum_{n=1}^{k}\mathbf{x}(n)\mathbf{x}(n)^{H}$$

$$\mathbf{r}_{xs}(n)=\frac{1}{k}\sum_{n=1}^{k}\mathbf{s}^{*}(n)\mathbf{x}(n)$$

k is number of observations

I have:

$$\mathbf{w}(n)=\mathbf{R}_{xx}^{-1}(n)\mathbf{r}_{xs}(n) \quad (3)$$

RLS Algorithm [3]:

$\mathbf{w}(0)=\mathbf{0}$

For n=1, 2,…

$$\mathbf{k}(n)=\frac{\mathbf{P}(n-1)\mathbf{x}^{*}(n)}{\gamma+\mathbf{x}^{T}(n)\mathbf{P}(n-1)\mathbf{x}^{*}(n)}$$

$$\mathbf{e}(n)=d(n)-\mathbf{w}^{T}(n-1)\mathbf{x}(n)$$

$$\mathbf{w}(n)=\mathbf{w}(n-1)+\mathbf{e}(n)\mathbf{k}(n) \quad (4)$$

$$\mathbf{P}(n)=\frac{1}{\gamma}\left(\mathbf{P}(n-1)-\mathbf{k}(n)\mathbf{x}^{T}(n)\mathbf{P}(n-1)\right)$$

Traditional CGM Algorithm [2]:

$\mathbf{r}(1)=d(1)\mathbf{ones}(N)-\mathbf{A}\mathbf{w}(1)$

with $\mathbf{A}=\mathbf{x}(1)\mathbf{x}^{H}(1)$

$\mathbf{p}(1)=\mathbf{r}(1)$

For n=1, 2,…

$$\mathbf{A}=\mathbf{x}(n)\mathbf{x}^{H}(n)$$

$$\alpha(n)=\mathbf{r}^{T}(n)\mathbf{r}(n)/\mathbf{p}^{T}(n)\mathbf{A}\mathbf{p}(n)$$

$$\mathbf{w}(n+1)=\mathbf{w}(n)-\alpha(n)\mathbf{p}(n) \quad (5)$$

$$\mathbf{r}(n+1)=\mathbf{r}(n)-\alpha(n)\mathbf{A}\mathbf{p}(n)$$

$$\beta(n)=\mathbf{r}^{T}(n+1)\mathbf{r}(n+1)/\mathbf{r}^{T}(n)\mathbf{r}(n)$$

$$\mathbf{p}(n+1)=\mathbf{r}(n+1)+\beta(n)\mathbf{p}(n)$$

Proposed CGM Algorithm in [2]:

$\mathbf{r}(1)=d(1)\mathbf{ones}(N)-\mathbf{A}\mathbf{w}$

with $\mathbf{A}=\mathbf{x}(1)\mathbf{x}^{H}(1)$

$\mathbf{p}(1)=\mathbf{r}(1)$

For n=2,3,…

$$\mathbf{R}(n)=\sum_{l=1}^{n}\mathbf{x}(l)\mathbf{x}^{H}(l)$$

$$\mathbf{w}(n)=\mathbf{w}(n-1)-\alpha(n)\mathbf{r}(n-1) \quad (6)$$

Với $\mathbf{r}(n)=\mathbf{p}(n)+\hbar(n)\mathbf{r}(n-1)$

$$\mathbf{p}(n)=\mathbf{p}(n-1)-\alpha(n)\mathbf{R}(n)\mathbf{r}(n-1)$$

$$\alpha(n)=-\left[\frac{\mathbf{r}^{H}(n-1)\mathbf{f}(n-1)}{\mathbf{r}^{H}(n-1)\mathbf{R}(n)\mathbf{f}(n-1)}\right]$$

$$\hbar(n)=-\left[\frac{\mathbf{f}(n)\mathbf{R}(n)\mathbf{r}(n-1)}{\mathbf{r}^{H}(n-1)\mathbf{R}_{k}(n)\mathbf{r}(n-1)}\right]$$

3. PROPOSED HIERARCHICAL CODEBOOK ALGORITHM

$S_0=2$

$\mathbf{H}_{fd}=0$

for l = 1 : L do

(searching two transmit and receive codewords)

for m = 1 : 2^{S_0} do

for n = 1 : 2^{S_0} do

$$\bar{y}(m,n) = \sqrt{P}\mathbf{w}_r(S_0,n)^H\mathbf{H} + z - \sqrt{P}\mathbf{w}_r(S_0,n)^H\mathbf{H}_{fd}$$

end

end

$$(m_t,n_r) = \arg\max_{(m,n)}|y(m,n)|$$

for s = $(S_0+1):S$ do

for m = 1,2 do

for n = 1,2 do

$$\bar{y}(m,n) = \sqrt{P}\mathbf{w}_r(s,2(n_r-1)+n)^H\mathbf{H} + z - \sqrt{P}\mathbf{w}_r(s,2(n_r-1)+n)^H\mathbf{H}_{fd}$$

end

end

$$(a,b) = \arg\max_{(m,n)}|y(m,n)|$$

$$m_t = 2(m_t-1)+a; n_r = 2(n_r-1)+b$$

end

for m = −1,0,1 do

for n = −1,0,1 do

$$y = \sqrt{P}\mathbf{w}_r(s,n_r+n)^H\mathbf{H} + z$$

$$\mathbf{H}_{fd} = \mathbf{H}_{fd} + y\mathbf{w}_r(s,n_r+n)$$

end

end

end

4. SIMULATION

Based on the above algorithms, we simulate a 4×4 MIMO antenna model used for 5G mobile communication systems. Here, the required number of loops for each algorithm and the generation of beamforming through the beam weight vectors. In the simulation, we use three physical paths with input parameters such:

Gain of paths : $\alpha = [1 \quad 0.5 \quad 0.5]$;

AoDs: $\varphi = [0.5\pi/8 \quad 1.5\pi/8 \quad 14.5\pi/8]$;

AoAs: $\theta = [0.5\pi/8 \quad 1.5\pi/8 \quad 14.5\pi/8]$;

Wavelength of signal: $\lambda = 0.01$ (m); Velocity of mobile: $\nu = 40$ (km/h); Transmit antenna spacing: $s_T = 0.05$ (m); Receive antenna spacing: $s_R = 0.05$ (m); Number of elements at transmit antenna: M=4 (using one beam formed by 4 antenna elements); Number of elements at receive antenna: N=4. Number of training symbols is 20 while number of data symbols is 30.

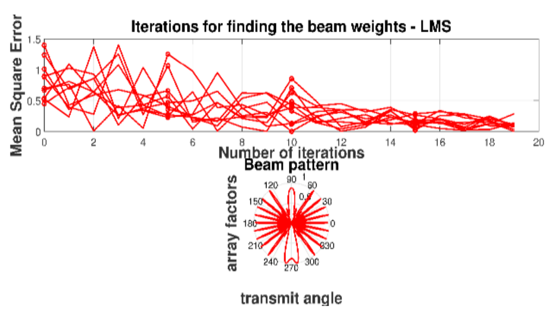

Figure 3. LMS: MSE and beam weights

With Figure 3, after ten attempts of creating the random input, the number of iterations is unstable and often significant.

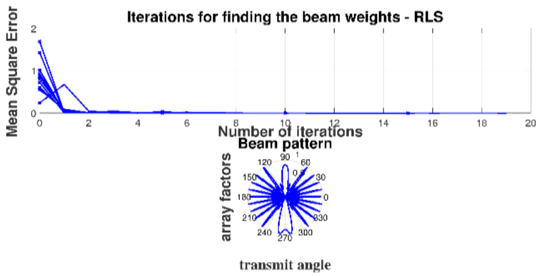

Figure 4. RLS : MSE and beam weights

As for Figure 4, the number of iterations is lower than the LMS but still high. It can take up to 6 iterations to have the optimal beam weights.

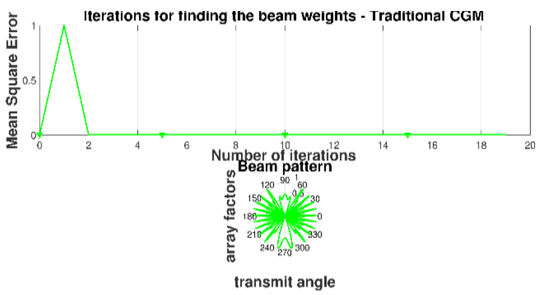

Figure 5. Tra. CGM : MSE and beam weights

In Figure 5, the number of iterations of traditional CGM is two, proving that the convergence of this method is better than LMS, RLS.

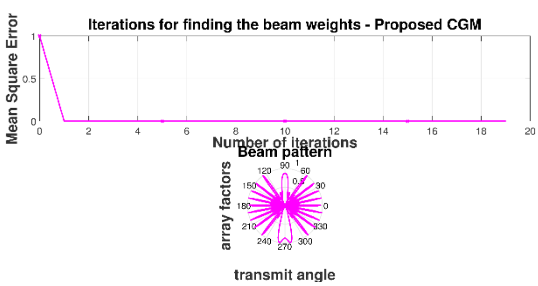

Figure 6. Pro. CGM : MSE and beam weights

The Proposed CGM shown in Figure 6 has the number of iterations of 1, which is lower than Tranditional CGM so the convergence speed is faster.

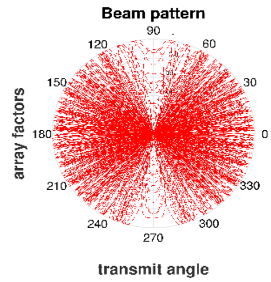

Figure 7. SMI: beam weights

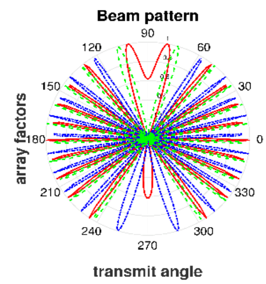

Figure 8. HC: beam weights

Figures 7 and 8 show two methods SMI and HC, respectively, The SMI describes the process of the inverse correlation matrix to find weight beams. This correlation matrix changes with the number of observations, so if we have 20 observations, we will have 20 corresponding beams for Figure 7. In the case of the SMI, we take the last beam (20th beam) for the capacity simulation in Figure 9. In the case of the HC case, there are three paths, so after using an improved search algorithm, we can find three optimum beams, which are also used in the simulation of Figure 9.

In addition to being interested in the number of iterations to find the optimum beam weights, we are also interested in how the beams generated by these weights affect the channel capacity. This is because the weight vectors will affect the antenna gain in the receive directions in a multipath environment. We compare the capacity for LMS, RLS [3], traditional and proposed CGM [2], and the proposed HC in this paper instances.

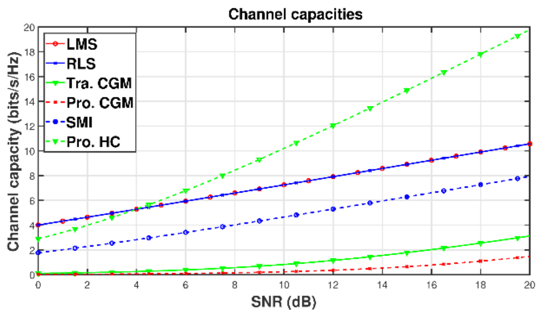

Figure 9. Capacities in cases of LMS, RLS, Tra. And Pro. CGM [2], SMI và Proposed HC

In Figure 9, we see that the channel capacity in the case of LMS and RLS is similar, although it is proven that RLS has a faster convergence rate than LMS, Traditional CGM has a higher channel capacity than Proposed CGM [2], although the convergence speed Proposed CGM's is faster. SMI has better capacity than the two cases above, but the new HC gives the highest channel capacity in SNR with large values of about 4-5 dB onwards.

5. CONCLUSION

The article covers the fundamental algorithms such as LMS, RLS, Traditional and Proposed CGM, and Proposed HC. We compare the capacity for LMS, RLS, traditional and proposed CGM, and the proposed HC. The proposed HC allows capacity to be significantly increased, especially with the high SNR. The article also shows how to generate receive beams using a hierarchical codebook for multipath environments.

ACKNOWLEDGMENT

This article is implemented as a requirement of the University-level research project, T2021-DT-009. I thank the University of Transport and Communications for this support.

REFERENCE

[1] SK Imtiaj, Iti Saha Misra, Sandipan Bhattacharya, Revisiting smart antenna array design with multiple interferers using basic adaptive beamforming algorithms: Comparative performance study with testbed results, Wiley, 2020.

[2] Veerendra Dakulagi, Mukil Alagirisamy, Adaptive Beamformers for High-Speed Mobile Communication, Wireless Personal Communications volume, Vol.113, No.7, 2020, pp. 1691–1707.

[3] Irma Zakia; Suhartono Tjondronegoro; Iskandar; Adit Kurniawan, Performance comparison of LMS and RLS adaptive array on high speed train delivered from High Altitude Platforms, International Conference of Information and Communication Technology (ICoICT), 2013. [3]

[4] Sonia Hokam, Anjali Dandekar, Ankita Tiwari, Gulafshaafreen Sheikh, An Overview of LMS Adaptive Beamforming Algorithm for Smart Antenna, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 5, Issue. 1, 2016.

[5] Joseph Paulin Nafack Azebaze, Elijah Mwangi, Dominic B.O. Konditi, Performance Analysis of the LMS Adaptive Algorithm for Adaptive Beamforming, International Journal of Applied Engineering Research, Vol. 12, No. 22, 2017, pp. 12735-12745.

[6] Revati Joshi, Adaptive Beamforming Using LMS Algorithm, International Journal of Research in Engineering and Technology, Vol. 03, No. 05, 2014, pp.589-593.

[7] Vivek Kumar, Deepak Rajouria, Manju Jain, Vikas Kumar, Performance Analysis of LMS Adaptive Beamforming Algorithm, IJECT, Vol. 4, Issue Spl - 5, 2013.

[8] Muhammad, C. B.; Anwar, K., Interference Mitigation using Adaptive Beamforming with RLS Algorithm for Coexistence between 5G and Fixed Satellite Services in C-Band, Journal of Physics: Conference Series, Vol. 1577, Issue. 1, 2020.

[9] Peter Chuku, Thomas Olwal and Karim Djouani, Adaptive Array Beamforming Using An Enhanced RLS Algorithm, International Journal on AdHoc Networking Systems (IJANS), Vol. 8, No. 1, 2018.

[10] L. Wang R.C. de Lamare, Constrained adaptive filtering algorithms based on conjugate gradient techniques for beamforming, IET Signal Processing, Vol. 4, No. 6, 2011, pp. 686 – 697.

[11] Zhenyu Xiao, Tong He, Pengfei Xia and Xiang-Gen Xia, Hierarchical Codebook Design for Beamforming Training in Millimeter-Wave Communication, IEEE Transactions on Wireless Communications, Vol.15, Issue.5, 2016, pp. 3380-3392.

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