Blind Array Algorithm Adaptation by CNN-assisted SIR Estimation using IQ Constellation

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SUMMARY This paper presents a blind interference suppression performance enabled by deep learning assisted interference estimation using visualized wireless signal information, that is, IQ constellation. Co-channel interference becomes more extensive due to frequency resource exhaustion and small cell deployment which had been triggered by mobile traffic explosion. Multi-antenna signal processing known as blind adaptive array (BAA) is an effective means to suppress co-channel interference without any a priori information such as channel state information. These algorithms, e.g. constant modulus algorithm (CMA) and power inversion (PI) should be optimally selected according to interference level. We previously verified the possibility of signal-to-interference (SIR) classification by multi-layered deep convolutional neural network (CNN), utilizing IQ constellation images where includes the desired and interference signals for model training. This paper clarifies the interference suppression performance of BAAs adaptively switched according to estimated SIR values.
key words: *Blind Adaptive Array, Interference Suppression, Constant Modulus Algorithm, Power Inversion, Convolutional Neural Network*

1. Introduction

The escalation in mobile traffic has led to increased co-channel interference, a result of the depletion of frequency resources and the proliferation of small cells. A solution for mitigating this interference, without needing prior knowledge like channel state information (CSI), is multi-antenna signal processing, specifically the blind adaptive array (BAA) approach. Notable methods in this category are the constant modulus algorithm (CMA) [1] and power inversion (PI) [2]. However, the effectiveness of these BAA algorithms is contingent on the signal-to-interference power ratio (SIR) at the array's input, necessitating optimal selection based on the level of interference. We verified the feasibility of SIR classification by the multi-layered deep convolutional neural network (CNN) [3], trained using IQ constellation images, containing both desired and interference signals. This study focuses on the interference suppression capabilities of these techniques, particularly their adaptive switching based on the estimated SIR.

The rest of this paper is organized as follows. Section 2 briefly describes the system model of interest and CMA and PI as BAAs. Section 3 presents the proposed scheme and evaluation results. Section 4 concludes this paper.

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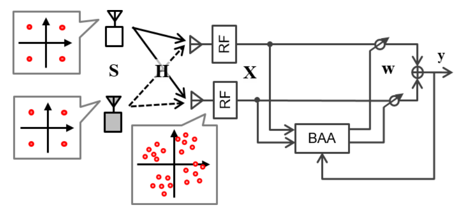

Fig. 1 System model.

2. Preliminaries

2.1 System description

Let N_t, N_r and N_s denote the number of transmitters, receiving antenna elements and modulated data symbols, respectively. Transmitter is assumed to have one antenna. Fig. 1 depicts a system model of interest. This study assumes a simplified channel model based on the plane wave approximation and a narrow band single carrier transmission. $\mathbf{S} = [\mathbf{s}_1^T \ \mathbf{s}_2^T]^T \in \mathbb{C}^{N_t \times N_s}$ is the transmission signal including all transmitters and $\mathbf{X} \in \mathbb{C}^{N_r \times N_s}$ is the received signal, i.e. array input. These relationship can be expressed as $\mathbf{X} = \mathbf{HGS} + \mathbf{N}$. Each element of $\mathbf{H} = [\mathbf{h}_1 \ \mathbf{h}_2] \in \mathbb{C}^{N_r \times N_t}$ is the channel coefficient, $\exp\{-\mathrm{j}2\pi(i-1)d\cos\theta_j\}$, from the j-th transmitter to the i-th receiver where θ represents an angle of arrival (AoA). $\mathbf{G} \in \mathbb{C}^{N_t \times N_r}$ is a diagonal matrix to represent the signal strength for each signal source, g_j. $\mathbf{N} \in \mathbb{C}^{N_r \times N_s}$ denotes the additive white Gaussian noise (AWGN). BAA weight, $\mathbf{w} \in \mathbb{C}^{N_r \times 1}$, is derived by respective BAA algorithms, and is multiplied to the received signal, $\mathbf{X}$, to obtain the array output, $\mathbf{y} = \mathbf{wX} \in \mathbb{C}^{1 \times N_s}$.

2.2 Blind adaptive array algorithms

A) Constant modulus algorithm (CMA): This study employs least square CMA (LS-CMA) which is known to exhibit good convergence characteristics [1]. Its update manner can be expressed as

$$\mathbf{y} = \mathbf{w}_{\mathrm{CMA}}^H(m)\mathbf{X}, \tag{1}$$

$$\mathbf{w}_{\mathrm{CMA}}(m+1) = \left(\mathbf{XX}^H\right)^{-1}\mathbf{Xe}_{\mathrm{CMA}}^H, \tag{2}$$

where $e_{\mathrm{CMA},k} = y_k/|y_k|$. CMA requires a condition in order to precisely suppress interference, that is, the desired signal must be captured at the initial condition. It indicates that input SIR must be larger than 0 dB.

B) Power inversion (PI): PI attempts to invert SIR of the received signal. Therefore it should be applied at SIR < 0 dB. The PI weights are obtained from the received signal's autocorrelation matrix as follows,

$$\mathbf{w}_{\mathrm{PI}} = (\mathbf{X}\mathbf{X}^H)^{-1}\mathbf{c}, \tag{3}$$

where $\mathbf{c} = (1,\ 0,\ \cdots,\ 0)^T$ is defined as the constraint vector.

3. Proposed Scheme and Performance

3.1 Proposal: CNN-based SIR classification

SIR should be blindly estimated to adaptively switch the above two algorithms in order to suppress arbitrary power of interference. Focusing on the IQ constellation, it can be seen that signal scattering varies depending on the interference level; dispersion is small when SIR is large and vice versa. In the supervised learning, we first obtain IQ constellation images and apply CNN to classify that SIR is larger than 0 or not. Our previous study verified its feasibility; more than 80% accuracy is achieved except for SIR= 0 dB [3].

3.2 Simulation result

There are two transmitting stations with one antenna, each radiating a desired signal and an interfering signal. The angle of arrival of each station is assumed to be randomly determined from $-90°$ to $90°$ every $0.01°$ with respect to the receiving station. The number of CMA iterations is set to 20. In PI, the CMA is subsequently applied to the derived PI weight as its initial value; interference suppression capability can be enhanced. Under the above conditions, the signal-to-interference plus noise power ratio (SINR) at the array output is evaluated. It is defined as

$$\mathrm{SINR} = \frac{g_1 \left\|\mathbf{w}^H \mathbf{h}_1 \mathbf{s}_1\right\|^2}{g_2 \left\|\mathbf{w}^H \mathbf{h}_2 \mathbf{s}_2\right\|^2 + \left\|\mathbf{w}^H \mathbf{N}\right\|^2}. \tag{4}$$

Fig. 2 shows the cumulative distribution function (CDF) of the array output SINR when input SIR = ±3 dB. The characteristics of CMA without SIR estimation and the minimum mean square error (MMSE) algorithm using a reference signal are also plotted as benchmarks. Classification accuracy is 100% at SIR = ±3 dB [3] and hence the algorithm is switched properly and the output SINR shows the same distribution as that of the conventional CMA at SIR = 3 dB.

Fig. 3 shows the array output SINR with respect to the input SIR. Here, CDF = 50% and 10% values are plotted, respectively. MMSE with a reference signal provides the desirable interference suppression performance irrespective of input SIR. Conventional CMA without SIR classification shows good output SINR only in SIR > 0 dB. Focusing on the median value of the proposed scheme, generally good SINR is obtained in the regions of |SIR| > 1 dB. For the CDF = 10% value, |SIR| > 2 dB can be the applicable range. SIR = 0 dB was not originally trained; an additional operation is required by classifying this region individually. The SINR tends to decrease the most at SIR = 0.5 dB, which is due to the different signal mixture models used for training from

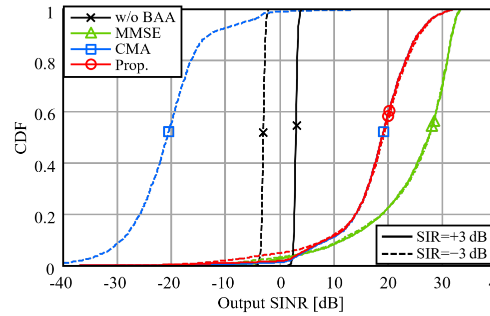

Fig. 2 CDF of array output SINR (Input SIR = ±3 dB).

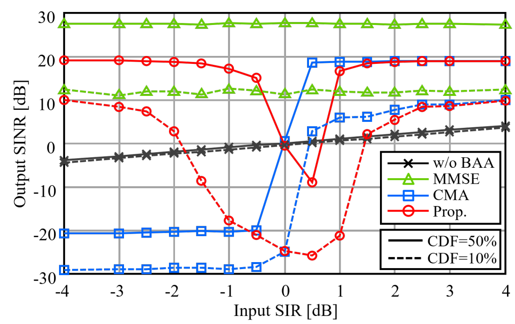

Fig. 3 Array output SINR versus input SIR.

the evaluation of BAA application. By adapting the model training to the application scenario, it is expected that the estimation accuracy can be further improved. Consider an OFDM scenario in which SIR estimation and CMA/PI are individually applied to each subcarrier, the proposed scheme could well work to stably obtain interference suppression performance.

4. Conclusion

This paper presented BAA interference suppression performance provided by CNN-based SIR classification using visualized IQ constellation images. CMA and PI were optimally chosen to suppress interference; its fundamental effectiveness has been validated.

Acknowledgments

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