Abstract—In this paper, an orthogonal stochastic gradient descent (O-SGD) based learning approach is proposed to tackle the wireless channel over-training problem inherent in artificial neural network (ANN)-assisted MIMO signal detection. Our basic idea lies in the discovery and exploitation of the training-sample orthogonality between the current training epoch and past training epochs. Unlike the conventional SGD that updates the neural network simply based upon current training samples, O-SGD discovers the correlation between current training samples and historical training data, and then updates the neural network with those uncorrelated components. The network updating occurs only in those identified null subspaces. By such means, the neural network can understand and memorize uncorrelated components between different wireless channels, and thus is more robust to wireless channel variations. This hypothesis is confirmed through our extensive computer simulations as well as performance comparison with the conventional SGD approach.

I. INTRODUCTION

Detection of multiple-input multiple-output (MIMO) signals through machine learning (ML) has demonstrated remarkable advantages in terms of their strong parallel-processing ability, good performance-complexity tradeoff, as well as self-optimization with respect to the dynamics of wireless channels [1]. More remarkably, data-driven ML approaches are model independent, i.e., they learn to detect signals without the need of an explicit model of the signal propagation (e.g., [2]–[4]). This is particularly useful for receivers to reconstruct signals from random nonlinear distortions, which are often very hard to handle with hand-engineered approaches. Meanwhile, ML-assisted wireless receivers can also be model-driven (e.g., [5]–[8]), which can take advantage of the model knowledge to mitigate the curse of dimensionality problem inherent in the deep learning procedure. Moreover, ML and hand-engineered approaches can work together to form a synergy when conducting the signal detection [9]–[13].

Despite already numerous contributions in this domain, there are very few results that have been reported so far, concerning the wireless channel over-training problem. More specifically, current ML-assisted receivers are trained mainly for a specific channel model; such as the MIMO Rayleigh-fading channel. However, a receiver that is well trained for one channel model is often too sub-optimum or even unsuitable for other channel models. This is also known as the training set over-fitting problem in the general artificial intelligence domain. In the literature, there are a couple of ways to handle the over-training problem. One approach is called continual learning, which aims to inject new knowledge without forgetting previously learned knowledge. As a consequence, machines will always adapt themselves to be better optimized for latest training samples (i.e. new channel models in telecommunications) [16]. The other approach is called multi-task learning [17] which aims to improve all training tasks simultaneously by combining their common features. These approaches have already achieved promising results in traditional ML applications, such as natural language processing or image/video recognition; however, it is still not clear whether these approaches can be cost-effective to handle wireless channels that are random, continuous, and infinite in their states.

In this paper, we introduce an orthogonal stochastic gradient descent (O-SGD) algorithm to tackle the wireless channel over-training problem when machines learn to detect communication signals in MIMO fading channels [1]. The basic idea lies in the discovery and exploitation of the orthogonality of training samples between the current training epoch and past training epochs. More specifically, the O-SGD algorithm does not update the neural network simply based upon training samples of the current epoch. Instead, it first discovers the correlation between current training samples and historical training data, and then update the neural network with those uncorrelated components. The network updating occurs only in those identified null subspaces. By such means, the neural network can understand and memorize uncorrelated components between different training tasks (e.g. channel models). This idea is evaluated for artificial neural network (ANN)-assisted MIMO detection with various channel models. It is shown, through computer simulations, that O-SGD is very robust to channel model variations as well as SNR variations.

II. SYSTEM MODEL AND PRELIMINARIES

A. MIMO System Model and Optimum Detection

Consider MIMO uplink communications, where $M$ transmit antennas simultaneously talking with $N$ receive antennas through the wireless channel ($N \geq M$). It is also assumed that the receive antennas can fully cooperate and share their received waveform for joint signal processing. The discrete-time equivalent baseband signal model can be described as the following matrix form

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{v}$$  \hspace{1cm} (1)

O-SGD is suitable for detecting communication signals in general cases. This paper focuses on the MIMO signal model for the sake of concise presentation and clear concept delivery.
where \( y = [y_0, \ldots, y_{N-1}]^T \) stands for the spatial-domain received signal block, \( x = [x_0, \ldots, x_{M-1}]^T \) for the transmitted signal block with zero mean and identical covariance \( \sigma_x^2 \). Each symbol of \( x \) is independently drawn from a finite-alphabet set \( \mathcal{A} \) with \( |\mathcal{A}| = L \), \( \mathbf{H} \in \mathbb{C}^{N \times M} \) for the MIMO channel matrix, and \( \mathbf{v} \) for the additive white Gaussian noise (AWGN) with \( \mathbf{v} \sim \mathcal{CN}(0, \sigma_v^2) \). Moreover, the superscript \(^T\) stands for the vector/matrix transpose, and \( \mathbf{I} \) for the identity matrix.

The general problem of MIMO signal detection is to form the decision \( \hat{x} \) based upon the received signal \( y \) and channel matrix \( \mathbf{H} \). The maximum-likelihood solution (or equivalently the sphere decoding) is integer least-squares (ILS) optimum by achieving the following objective function

\[
\hat{x} = \arg \min_{x \in \mathcal{A}^M} \| y - \mathbf{H}x \|^2
\]

where \( \| \cdot \| \) stands for the Euclidean norm.

### B. On Scalability of ANN-assisted MIMO Detection

In the ML theory, the ILS problem in (2) is actually a Bayesian optimization problem. The basic principle can be described as:

**Proposition 1 (See [4]):** Given the MIMO channel matrix \( \mathbf{H} \) and the finite-alphabet set \( x \in \mathcal{A}^M \), ML is able to establish the link between \( y \) and \( \mathbf{H}x \) according to the maximum \( a \) posteriori probability \( p(\mathbf{H}x|y) \).

If the MIMO channel \( \mathbf{H} \) is fixed, we have the maximum \( a \) posteriori probability \( p(\mathbf{H}x|y) = p(x|y) \). The size of the finite-alphabet set grows exponentially with the number of transmit antennas and polynomially with the modulation order. Despite very high complexities for a large-MIMO, the ML procedure can be managed by employing the high-performance parallel computing technology.

ML signal detection faces great challenges when the MIMO channel matrix is randomly time-varying; as in this case, the set of possibly received signals becomes infinite. More seriously, the randomness of MIMO channel will result in the channel ambiguity, i.e., the receiver’s observation \( y \) might correspond to various combinations of the channel matrix \( \mathbf{H} \) and the transmitted signal block \( x \) even in the noiseless case. In this case, ML is not able to conduct signal classification since the bijection between \( y \) and \( x \) is no longer hold. Theoretically, the channel ambiguity can be resolved by feeding the machine with the full channel knowledge, i.e., the input to the ANN-assisted MIMO receiver consists of the received signal block \( y \) as well as the channel matrix \( \mathbf{H} \) or more precisely its vector-equivalent form \( \hat{\mathbf{H}} \), which is often called the data-driven approach [18]. However, the dimension of the \( \mathbf{H} \)-defined training input grows much faster than the \( y \)-defined training input, and this could result in inefficient learning at the ANN training stage [19]. In this regard, the model-driven approach demonstrates remarkable advantages by replacing the received signal block \( y \) with its matched filter (MF) equalized version \( \mathbf{H}^H \mathbf{y} \) and the channel matrix \( \mathbf{H} \) with the corresponding version \( \mathbf{H}^H \mathbf{H} \); please see the block diagram of the ANN-assisted MIMO detection in Fig. 1. By such means, the growth rate for both inputs is largely scaled down.

The ANN employed here is a fully-connected feedforward neural network. The input to the ANN is \( c_0 = [\hat{\mathbf{H}}^T, (\mathbf{H}^H \mathbf{y})]^T \), where \( \hat{\mathbf{H}} \) is obtained by reshaping the matrix \( \mathbf{H}^H \mathbf{H} \) into a vector. Assume the entire network consists of \( K \) layers, ML algorithm conducts the output through \( K \) iterative steps. Denote \( \omega_k = \{\mathbf{W}_k, \mathbf{b}_k\} \) to the learning parameters of the \( k \)th layer, where \( \mathbf{W}_k \) and \( \mathbf{b}_k \) stand for the weight and bias, respectively. The stochastic objective function for the \( k \)th layer can be described by

\[
c_k = \sigma_k(\mathbf{W}_k \hat{s}_k - \mathbf{b}_k), \quad k=1,2,\ldots,K
\]

where \( \sigma_k(\cdot) \) is activation function, and \( c_k \) is the output of \( k \)th layer. The most commonly used activation function for hidden layer is called rectified linear unit (ReLU), which performs a threshold operation to each element of the input. Meanwhile, the activation function of output layer is decided by the referenced training target. In MIMO signal detection, the supervised training target is the original information bit \( s \), which is either 0 or 1. Therefore, standard logistic function (i.e. Sigmoid) is employed, which returns a value monotonically increasing from 0 to 1. By making hard decision on the Sigmoid output, we are able to obtain the ANN estimate \( \hat{s} \) of the original information bits. Prior to the use of ANN for MIMO signal detection, the ANN is trained with the aim of minimizing the following objective function

\[
\mathcal{L}_c(\omega) = \frac{1}{S} \sum_{i=1}^{S} \mathcal{L}(s_i, \hat{s}_i), \quad \forall k
\]

by adjusting learning parameters \( \omega_k \), where \( \mathcal{L}(\cdot) \) stands for loss function, and \( S \) for the size of the set which contains all input-output training pairs. Moreover, the most popular algorithm to find good set of \( \omega_k, \forall k \) is called stochastic gradient descent (SGD), which can be mathematically described by the following function

\[
\omega_k = \omega_k - \eta \nabla f(\omega_k), \quad \forall k
\]

where \( \eta > 0 \) stands for learning rate, and \( \nabla f(\omega) \) for the stochastic gradient.

### C. The Channel Over-Training Problem

**Definition 1 (channel over-training):** It is called channel over-training problem in ANN-assisted MIMO signal detection, when an ANN optimized for a specific channel model (e.g. Rayleigh fading) is too sub-optimum or even unsuitable for other channel models.
The channel over-training problem significantly limited the application of ANN-assisted MIMO detection in real practice. Potential solution towards this problem is to contentiously training the new channel model on the previous trained ANN. However, it might cause catastrophic forgetting problem, i.e., ANN has a tendency to forget previously learned knowledge when they get trained on new tasks \[20, 21\]. This is reasonable since there is a shifting of input distribution across different tasks. In other words, the conventional optimization techniques converges to radically different solutions when different tasks with less common factors or structures in the input are presented to the ANN. To tackle this issue, continual learning has been proposed, which aims to inject new knowledge without forgetting previously learned knowledge. The learning process of different tasks are operated sequentially in time series. Notable continual learning approaches include:

1) Fine-tuning \[22\]: modifies the parameters of an existing ANN for the new tasks by extending the output layer with randomly initialized neurons. For the new tasks, learning rate is set to a relatively smaller value in order to mitigate its impact on the previously learned task.

2) Network extending \[23\]: adds extra neurons on each layer to prevent the loss of previously learned knowledge while new discriminative features come in. The disadvantage of this method lies in the substantially increasing number of parameters in the ANN, thereby results in a performance decrease compares with the fine-tuning algorithm.

3) Super neural network \[24\]: partitions a giant network into a number of sub-networks, with each optimized for a specific training set/task.

In addition to continual learning, a ML paradigm called multi-task learning \[17\] is able to accomplish largely the same thing. The idea lies in the use of common features contained in multiple related tasks to help improve the generalization performance of all tasks. Therefore, the learning process of different tasks are operated simultaneously in time domain.

Despite already remarkable achievements, the current state-of-the-art approaches are mainly designed for the conventional ML applications, such as image processing and speech recognition. However, they are not cost-effective to handle wireless communication channels that are random, continuous and dynamic in their states. There is a need of a cost-effective solution that solve the channel over-training problem without complicating the ANN architecture. This motivates the development of the O-SGD algorithm in this paper.

III. THE ORTHOGONAL-SGD ALGORITHM

The basic idea of O-SGD lies in the discovery and exploitation of the orthogonality of the training samples between the current training epoch and previous training epochs. Specifically, the O-SGD algorithm does not update the neural network simply based upon the current training input. Instead, it discovers the correlation between the current training samples and the historical training data. By such means, the ANN can understand and memorize uncorrelated components between different training data set. Please see Algorithm 1 for the pseudo-code of the proposed O-SGD algorithm.

Denote \(f(\omega_k)\) to a noisy stochastic objective function with respect to the parameter \(\omega_k\), as we have introduced in \[1\], where the subscript \([i]\) stands for the layer number. The aim of ANN training process is to minimize the expected value of the objective function \(\mathbb{E}[f(\omega_k)]\) by adjusting the network parameters \(\omega_k\).

In O-SGD, the first step is to calculate the correlation between the current input \(c_{k-1}^i\) and all previous training data. Mathematically, it can be done by forming all previous input training data as a matrix \(A\) and calculating the direction orthogonal to the space of matrix \(A\) by

\[
\Psi_k = I - A(A^TA + \alpha I)^{-1}A^T
\]

where \([\cdot]^{-1}\) stands for the vector/matrix inversion, and \(\alpha\) is a relatively small constant. The direction-modified gradient is then determined by

\[
\nabla f(\omega_k)' = \nabla f(\omega_k) \cdot \Psi_k
\]

where \(\nabla f(\omega_k)\) is the gradient obtained by the conventional SGD algorithm. However, the computational

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**Algorithm 1**: The proposed O-SGD algorithm together with clipping-rate learning algorithm for stochastic optimization in ANN-assisted MIMO signal detection. Recommended parameters are \(\eta_1 = 0.001\), \(\eta_2 = 10^{-5}\), \(\lambda = 1\), \(\beta = 100\), \(\beta_1 = 0.9\), \(\beta_2 = 0.999\), \(\epsilon = 10^{-8}\).

**Input**: \(\eta_1\): initial learning rate

**Input**: \(\eta_2\): lower bound learning rate

**Input**: \(\lambda\): forgetting factor

**Input**: \(\epsilon\): compensation factor

**Input**: \(c_{k-1}^i\): input to the \(i\)th layer at time slot \(t\)

**Input**: \(f(\omega_k)\): stochastic objective function

**Input**: \(\beta_1, \beta_2 \in [0, 1]\): exponential decay rates for the moment estimates

**Initialization**: \(\omega_k, \Psi_k = I_k/\beta, \mathbf{m}_k = 0, \mathbf{v}_k = 0, t = 0\)

while \(\omega_k\) not converged do

\[
\begin{align*}
p_k &= \Psi_k c_{k-1}^i / (\lambda + c_{k-1}^i T \Psi_k c_{k-1}^i) \\
\Psi_k &= \lambda^{-1} \Psi_k - \lambda^{-1} p_k c_{k-1}^i T \Psi_k \\
g_k &= \nabla f(\omega_k) \cdot \Psi_k \\
\mathbf{m}_k &= \beta_1 \mathbf{m}_k + (1 - \beta_1) \cdot g_k \\
\mathbf{v}_k &= \beta_2 \mathbf{v}_k + (1 - \beta_2) \cdot g_k^2 \\
\hat{\mathbf{m}}_k &= \mathbf{m}_k / (1 - \beta_1^k) \\
\hat{\mathbf{v}}_k &= \mathbf{v}_k / (1 - \beta_2^k) \\
\eta_t &= \max(\eta_1 / \sqrt{t}, \eta_2) \\
\omega_k &= \omega_k - \eta_t \cdot \hat{\mathbf{m}}_k / (\epsilon + \sqrt{\hat{\mathbf{v}}_k})
\end{align*}
\]

end

**Output**: \(\omega_k, \forall k\)
complexity and memory requirement for such an approach continue to increase over time, which makes it unsuitable for real practise. Inspired by the recursive least-square (RLS) algorithm in adaptive filter theory [25], we improve the O-SGD algorithm by considering each time step as an independent task and updating $\Psi_k$ through an iterative manner

$$p_k = \Psi_k c_{k-1}^T / (\lambda + c_{k-1}^T \Psi_k c_{k-1})$$
$$\Psi_k = \lambda^{-1} \Psi_k - \lambda^{-1} p_k c_{k-1}^T c_{k-1} \Psi_k$$

(8)

where $c_{k-1}$ is the input to the $k$th layer at time step $t$, $\lambda$ is the forgetting factor, and $\Psi_k$ is initialized as $\Psi_k = I_k / \beta$, where $\beta$ is a constant number. It is perhaps worth noting that $\Psi_k$ is layer-specific, each layer has to compute it independently based on the input $c_{k-1}$. By such means, neural network does not need to store all previous training data, instead only the previous gradient projection matrix $\Psi_k$ is needed.

The second step is to update the network parameters by employing the first-order gradient-based optimization approach. The most commonly used algorithm is Adam [26]. However, researchers have recently found that Adam can fail to converge to an optimal solution even in simple one-dimensional convex settings [27]. Meanwhile, we also observed the convergence difficulties in the training process of ANN-assisted MIMO signal detection. To tackle this issue, we designed a low-complexity clipping-rate optimization algorithm which takes the merits of the original Adam algorithm and mitigates the non-convergence problem particularly at the end of the training stage. The learning rate clipping function can be described as

$$\eta_t = \max(\eta_t / \sqrt{t}, \eta_l)$$

(9)

where $\eta_t$ is the initialized learning rate and $\eta_l$ is the lower bound of the learning rate. In this paper, we set $\eta_t = 0.001$ and $\eta_l = 10^{-5}$, as the above configuration is found to provide the best performance in our computer simulations.

IV. SIMULATION RESULTS AND EVALUATION

This section presents the experimental results and related analysis. The training data set and experimental settings are firstly introduced, followed by three experiments which aim to demonstrate our hypotheses in previous sections.

A. Data Sets and Experimental Setting

In conventional ML applications, such as image processing and speech recognition, different algorithms are evaluated under common benchmarks or data sets. However, wireless communication system normally deals with artificially manufactured signals which can be accurately generated. Thereby, we prefer to define the communication system model instead of providing specific training data sets.

In order to explore the channel over-training problem inherent in ANN-assisted MIMO signal detection, the performance of different algorithms are evaluated under multiple Rician fading channels with different values of $K$, where $K$ denotes the ratio between the power in the direct path (i.e. line-of-sight) and the power in the scattered paths (i.e. non-line-of-sight). The probability density function (PDF) of Rician distribution can be described by

$$f(x|\nu, \sigma^2) = \frac{x^\nu e^{-x^2/2\sigma^2}}{\sigma^2 \sqrt{\pi I_0(\nu)}}$$

(10)

with $\nu = K\Omega/(K + 1)$ and $\sigma^2 = \Omega/(2(K + 1))$, where $I_0(\cdot)$ is the modified Bessel function of the first kind with order zero, and $\Omega$ is the total power from both paths which is normalized to one. Moreover, we assume that the value of $K$ randomly varies in the range of $[0, 5]$. When $K$ equals to 0, the channel model becomes Rayleigh fading which has been widely used in state-of-the-art.

Recall the ANN architecture in Fig. 1 the transmitted signal block $x$ is the modulated information bits $s$. Channel coding is not considered in our simulations, but it can be straightforwardly implemented on the proposed architecture with no performance penalty. At the receiver side, the signal block is firstly proposed by the conventional MF equalizer; and then, together with the vector-form channel knowledge $\hat{h}$, serves as the input to the ANN. It is perhaps worth noting that the received signal as well as the channel knowledge are complex-valued, however most of the ML algorithms are designed by using real-valued numbers. To facilitate the operation of ANN, the complex-valued signal block is represented by the real-valued block with double the size (i.e. real and imaginary parts are concatenated). As far as the supervised learning is concerned, each training input should be paired with a supervisory output. In this paper, the referenced training target is set to be the original information block $\hat{s}$ as we have introduced in Section II-B. The detailed layout of ANN for MIMO signal detection can be found in Table 1.

All the experiments are run on a Dell PowerEdge R730 2x 8-Core E5-2667v4 Server, and implemented in MATLAB.

| TABLE I |
| --- |
| **LAYOUT OF THE ANN USED IN ALL EXPERIMENTS** |
| **Layer** | **Output dimension** |
| Input | $2M(M + 1)$ |
| Dense + ReLU | 512 |
| Dense + ReLU | 256 |
| Dense + ReLU | 128 |
| Dense + Sigmoid | $M \log L$ |

B. Simulation and Performance Evaluation

Our computer simulation are structured into three experiments. The first experiment aims to demonstrate our hypothesis on the existence of the channel over-training problem in ANN-assisted MIMO signal detection. Experiment 2 and 3 evaluate the performance of the conventional SGD algorithm and the proposed O-SGD algorithm by training multiple tasks sequentially and simultaneously in time domain, respectively. The size of the MIMO system is 4-by-8, and QPSK modulation is considered at the transmitter side. The key metric utilized for performance comparison is the average BER over sufficient Monte-Carlo trails of multiple block fading channels. Moreover,
the signal-to-noise ratios (SNR) is defined as the average received information bit-energy to noise ratio per receive antenna (i.e. $E_b/N_0$).

**Experiment 1:** In this experiment, an ANN-assisted MIMO receiver optimized for Rayleigh fading channel (i.e. $K = 0$) is evaluated under multiple other channel models. The aim of this experiment is to demonstrate the existence of channel over-training problem in ANN-assisted MIMO signal detection. Moreover, the training is operated at $E_b/N_0 = 8$ dB with a mini-batch size of 500; as the above configurations are found to provide the best performance.

Fig. 2 shows the average BER performance of the ANN-assisted MIMO receiver trained by SGD algorithm. The baseline for performance comparison is the optimum maximum-likelihood sequence detection (MLSD). It is shown that the ANN-assisted MIMO receiver achieves near-optimum performance under trained channel model (i.e. $K = 0$); the performance gap to the MLSD is almost negligible. However, the detection performance significantly decreased when other channel models are considered (i.e. $K = 1, 2, 3, 5$). The performance gap between the ANN-assisted MIMO receiver and MLSD is more than 10 dB at high SNR regime. The above phenomena coincides with our hypothesis that the channel over-training problem exists in the ANN-assisted MIMO signal detection.

**Experiment 2:** In this experiment, ANN-assisted MIMO receiver is firstly trained under Rayleigh fading channel (i.e. $K = 0$) by using either SGD or O-SGD algorithm. After training converge, a new training task (i.e Rician fading channel with $k = 1$) is operated on the previously trained ANN. The detection performance is evaluated under both channel models. The training $E_b/N_0$ is set at 8 dB and the size of the mini-batch is 500.

Fig. 3 shows the average BER performance of the ANN-assisted MIMO receiver trained by either SGD or O-SGD algorithm. The baseline for performance comparison is the optimum MLSD. It is shown that SGD algorithm fails to remember the previously learned knowledge, as the BER performance for the first task (i.e. $K = 0$) is around 9 dB away from MLSD at BER of $10^{-2}$. Conversely, it achieves a near-optimum performance for the second channel model (i.e. $K = 1$). The gap between MLSD and SGD is less than 1 dB at BER of $10^{-5}$. On the other hand, the proposed O-SGD algorithm shows promising learning capabilities for both tasks. The performance gaps to the optimum MLSD are 1.2 dB and 1.4 dB at BER of $10^{-2}$ for $K = 0$ and $K = 1$, respectively. It is also observed that the first task slightly outperforms the second task by around 0.5 dB at BER of $10^{-4}$. The above phenomena demonstrates our hypothesis in Section II-C that the proposed O-SGD algorithm is able to mitigate the channel over-training problem, but SGD can not.

**Experiment 3:** In this experiment, ANN-assisted MIMO receiver is trained under a mix of multiple Rician fading channel models in the range of $K \in [0, 5]$, and evaluated under a number of selected channel models.
Fig. 4 shows the average BER performance of the ANN-assisted MIMO receiver trained by either SGD or O-SGD algorithm. The baseline for performance comparison is the optimum MLSD. It is shown that the proposed O-SGD algorithm achieves promising detection performance under all the selected channel models (i.e., $K = 0, 1, 2, 3, 5$). The gap between MLSD and O-SGD is less than 1 dB. By contraries, SGD fails to conduct a good signal detection specifically at high SNR regime. The gap to the optimum MLSD is around 2.5 dB at BER of $10^{-3}$ for $K = 0$ and $K = 1$, and more than 5 dB for the other three channel models. This phenomenon indicates that the proposed O-SGD algorithm is able to achieve promising performance when multiple tasks are learned simultaneously.

V. CONCLUSION

In this paper, a novel O-SGD algorithm has been introduced to handle the channel over-training problem inherent in the ANN-assisted MIMO signal detection. It has been shown that O-SGD can discover the orthogonality between the current training epoch and previous training epochs, and update the neural network by exploring the uncorrelated components among different training tasks. Simulation results have shown that the proposed O-SGD algorithm significantly outperforms the conventional SGD algorithm under multiple channel models.

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