UAV intelligent optical communication based on conditional generation against network

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Abstract. This paper first introduces the advancement and importance of laser communication technology for drones., then introduced Deep Neural Network (DNN) to develop wireless end-to-end communication systems. Accurate channel state parameters (CSI) are necessary for computing DNN, but in laser communication systems, channel information is difficult to gain in advance or changes quickly with time and environment. This paper will use conditional generation network (GAN) to represent channels. The coded signal of the transmitter and the pilot data are used as condition information. By simulating the simulation results of the lognormal channel, the method can achieve high-quality transmission without clear CSI.

1. Introduction

Unmanned Aerial Vehicle referred to UAV, was first produced in the 1920s, because of its low cost and maintenance cost, low ground support requirements, small security risk coefficient, etc. In the field of UAV communication, a lot of original data needs to be losslessly transmitted. Some devices have a transmission rate requirement of 3-5 Gbps. However, the maximum transmission rate that can be achieved by microwave transmission is only Gbps. Therefore, it is impossible to use the existing microwave transmission system to perform non-destructive real-time transmission of these images and data, thereby greatly limiting the reconnaissance capability of the drone, and in addition, the directional stealth transmission, the space high-speed networking, the light and small, and the low Demand driven by power and technology development is also forcing the replacement of drone communication methods.

In the existing communication link, the laser communication link has large bandwidth capacity, strong transmission concealment, fast transmission rate, good anti-interference ability, flexible link networking form, small terminal size, lightweight and low power consumption. It is an important direction for the replacement of drone communication methods. However, the biggest problem is that UAV mainly flight in the atmosphere, the atmospheric medium is non-uniform, non-uniform density and temperature will change when carrying out a communication task, will cause atmospheric refractive index occurs Random changes, the channel state is unstable, it is difficult to predict, and it is difficult to guarantee the quality of communication. Intelligent communication refers to a communication on the basis of the depth of the neural network (DNN) should be used to develop end communications systems, mainly used to train the transmitter and receiver, but DNN requires precise instantaneous CSI to optimize the transmitter’ gradient to complete higher-quality model training. In this paper, the DNN method based on conditional generation network (GAN) is proposed. The
Conditional generation adversarial network for developing end-to-end wireless communication systems without accurate CSI.

2. Conditional GAN modeling channel

Most existing laser communication systems use digital communication technology, and the structure diagram of which is shown in Figure 1. Although this system is a very mature technology, one of each module is designed separately, generally have different goals and assumptions, it is difficult to ensure that the global optimum of the system. Further, the propagation channel is assumed to be embedded in the design of mathematical model representation, the hypothetical model does not reflect totally real channel, and affect the overall effect of the transmission system to a great extent. Lately, deep learning (DL) has been used to improve the performance of traditional communication systems, including channel estimation [2], and channel decoding [3]. Moreover, the deep-learning-based approach displays long-term improvements through processing blocks’ joint optimization, such as joint channel coding, and source coding [5]. However, the traditional DNN can only be well trained with known CSI, but the drone laser communication passes through the complex atmospheric channel, and the channel state information (CSI) is unstable and changing quickly.

The end-to-end system uses DNN to learn the implementation of the transmitter and receiver. The system block diagram is shown in Figure 2. The source enters the channel through the automatic encoder, and the gradient information is fed back to the automatic decoder to perform DNN weight training. But the back-propagation weights to train DNN are stopped in the channel, which prevents the normal end-to-end learning progress. To solve this problem, we use conditional generation adversarial networks (CGAN) to train the channels. In this section, CGAN is introduced and how conditional GANs are used to simulate real channels.

2.1. condition GAN

GAN is a new distributed learning generation method whose goal is to learn a sample model that can generate near-certain target - $P_{data}$ distribution. In this system, GAN is used to simulate the channel’ output, after that the trained model is used as an alternative to the real channel, then ensure smooth gradient transfer.
The structure diagram of the GAN is as Figure 3 shows, in which a minimum-maximum two-player game is formed presence in the generator (G) and the discriminator (D). The D is used to judge the specimen form the G or the real specimen, and G is used to generate the data that cheats D. During training, the G maps the input noise z and \( P(z) \) to the previous distribution to the samples, after that, collecting the specimens from the G and the real data to train the D to maximum discriminator capability. If the D classifies the specimens sources form successfully, this success can provide feedback to the G, then the G will make the learning generation more similar to the real sample.

The training process will end when equilibrium is reached, at equilibrium discriminator D cannot distinguish between real specimens and the fake data generated by D no better than random guesses. The goal of optimization is

\[
\min_D \max_G V(D,G) = \mathbb{E}_x[p_{data}(x) \log D(x)] + \mathbb{E}_z[p_{z}(z) \log (1 - D(G(z)))]
\]

(1)

Discriminator D object when the real part of the input data set is given a high value when the output of the generator G is given a low value is produced, and the G of the object is to maximize the output similar to real samples generate samples, discriminator The value of D is \( G(z) \). If both G and D are conditional in some additional data m, the GAN model can be spread to the CGAN model. The structure of the condition GAN is as Figure 4 shows. We just demand to adjust the message m as an additional input the G and the D. Then the output G of the generator will become \( G(x|m) \), and the output D of the discriminator will become \( D(x|m) \). Goal of optimization becomes

\[
\min_D \max_G V(D,G) = \mathbb{E}_x[p_{data}(x|m) \log D(x|m)] + \mathbb{E}_z[p_{z}(z|m) \log (1 - D(G(z|m)))]
\]

(2)

2.2. channel modeling

Generating adversarial networks is a powerful tool for learning channel output and distribution. Given a input x, the conditional distribution \( p(y|x) \) determines output y. Thus, by x is used as the condition information, the CGAN can be used to learn the output information of the channel. The G
will attempt to generate a sample similar to the actual channel output, and the D will attempt to divide the data from real specimens or the generator. In the CSI, $H$ can be considered of the sample, and also the receiver data important coherent detection. So as to obtain CSI, the usual method is to transmit message to the receiver and judge the CSI from the received information. In method of this paper, in adjustment information can add the received information $y_p$ such that the output $y$ changes with the received pilot data $y_p$ and the given information of $x$.

3. End-to-end communication system

By CGAN method, the sender can get the gradient. After completing previous work \cite{6}, the transmitted signal came from the finitely scatter set of size $M$ is changed to a single thermal length $M'$ vector $s'$\cite{7}, moreover, the end-to-end system is considered a problem of $M$ level sort. The receiver' output $s$ is a $M$ possible' probability vector. T cross-entropy loss means\cite{8}:

$$L = \sum_{n=1}^{M} S_n \log(\hat{S}_n)$$

(3)

Wherein $S_n$ and $\hat{S}_n$ stand for the $s$ and $\hat{s}$ of n-th elements.

The proposed training and testing end-to-end system structure diagram are as Figure 5 shows. During training, the signal transmitted is randomly generated and instantaneous CSI is obtained from random sampling \cite{9}. By the data for training, the receiver, transmitter and the G in the CGAN will be iteratively trained\cite{10}.

![Training Receiver & Testing](image)

**Training Receiver & Testing**

- $\xrightarrow{S}$ Transmitter $\xrightarrow{X}$ Receiver $\xleftarrow{Y}$ End-to-end loss for Receiver

**Fig. 5: Receiver, transmitter, generator training structure**

When training receivers and transmitters\cite{11}, the goal is to minimize end-to-end losses\cite{12}. For training, the purpose is to generate a channel strip member GAN minimized minimum-maximum optimization target\cite{13}.

3.1. Receiver training

Due to the loss function is calculated at the receiver, in which can be easily trained, and the gradient’ loss will be get easily. The DNN’ input are received specimen $y$ and the pilot specimen $y_p$.

In time-varying signal paths, through taking the received specimen $y$ together with the pilot specimen $y_p$ as input, the receiver will complete training.

3.2. Transmitter training

Since the channel generator is an analog channel, the transmitter training is similar to the receiver training. The cross-entropy loss is calculated at the receiver and the gradient is propagated back to the
transmitter by the CGAN. The transmitter’s weight will update based on the random gradient descent (SGD) while maintaining the condition GAN and the weight of the receiver.

3.3. Channel Generator training
The G is trained by the transmitter and the D. And actual data is obtained through the actual channel using the encoded signal from the transmitter while obtaining dummy data from the channel generator’s encoded data.

4. Simulation experiment
In this section, a signal lognormal channel propagation output results of the simulation. We compare the method based on channel-independent learning CGAN with the traditional method based on channel transfer function design. Table 1 lists the parameters and the structure of each model. The weights are updated by the Adam optimizer, furthermore, the training batch size is 320.

| Parameters               | Values       |
|--------------------------|--------------|
| Transmitter hidden layers| 32, 32       |
| Learning rate             | 0.001        |
| Receiver hidden layers    | 32, 32       |
| Learning rate             | 0.001        |
| Generator hidden layers   | 128, 128, 128|
| Learning rate             | 0.0001       |
| Discriminator hidden layers| 32, 32, 32  |

The lognormal channel belongs to one of the atmospheric turbulence channels, and its channel output is determined by the channel fading coefficient. Due to the signal path is time-varying, the noise is random, therefore, the G and receiver add condition information. The coherent detection task can be performed with a real number h, or pilot data can be added to the joint channel detection and estimation. We first test the validity of the CGAN in the standard 16QAM as the channel distribution of the coded symbols. Figure 6 shows signal constellation of the Lognormal channel. As can be seen from the figure, the strip member GAN can generate samples according to condition information in various manners.

![Figure 6: Signal constellation at the output of the Lognormal channel represented by condition GAN.](image)

On the number of channels end on the BER FIG performance 7 as shown, based on the depth of learning methods to obtain a block error rate (the BLER) and the signal-error performance of a conventional method is almost the same. That is, the DNN based on the condition GAN. The method can achieve good end-to-end communication performance under lognormal channel conditions.
5. Conclusion
UAV has unparalleled advantages as a communication carrier, and UAV laser communication has strong mobility, large bandwidth capacity, strong transmission concealment, fast transmission rate, good anti-interference ability, and flexible link networking. Terminal small size, lightweight, low power consumption, etc. is high hopes. Intelligent communication refers to a communication on the basis of the DNN be used to develop end communications system, primarily used to train the transmitter and receiver, but DNN requires accurate the instantaneous CSI to optimize transmitter Gradient to complete higher-quality model training. However, CSI is difficult to obtain and the time and location of the occurrence of a change in many communication systems. In this paper, we propose a conditional GAN method to complete the end-to-end learning of systems without clear channel state information (CSI). By lognormal simulation channel indicating: condition based on GAN ‘s DNN can be done efficiently without a clear method of channel state information (CSI) communication system, the study end, and which can achieve the BER performance of traditional methods.

The method proposed in this paper makes the realization of UAV intelligent optical communication possible. Although the simulation is based only on the lognormal channel, it also works in other channels, which opens up new ideas for building intelligent communication systems. However, more research is needed on the problem of whether the learning rate and the number of hidden layers are optimal when applying DNN.

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