Deep learning-based channel estimation for wireless ultraviolet MIMO communication systems*

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(Received 12 April 2023; Revised 3 July 2023)

To solve the problems of pulse broadening and channel fading caused by atmospheric scattering and turbulence, multiple-input multiple-output (MIMO) technology is a valid way. A wireless ultraviolet (UV) MIMO channel estimation approach based on deep learning is provided in this paper. The deep learning is used to convert the channel estimation into the image processing. By combining convolutional neural network (CNN) and attention mechanism (AM), the learning model is designed to extract the depth features of channel state information (CSI). The simulation results show that the approach proposed in this paper can perform channel estimation effectively for UV MIMO communication and can better suppress the fading caused by scattering and turbulence in the MIMO scattering channel.

Document code: A **Article ID:** 1673-1905(2024)01-0035-7

DOI https://doi.org/10.1007/s11801-024-3069-6

Wireless ultraviolet (UV) scattering communication can realize non-line-of-sight (NLOS) information transmission and meet the needs of some special communication scenarios[1]. However, due to its strong scattering characteristics, UV communication has the problems of pulse broadening and channel fading[2], the transmission power of the signal is limited, and the channel multiplexing rate is low. Introducing multiple-input multiple-output (MIMO) technology[3] to wireless UV communication, multiple transmitters and receivers are used to combat pulse broadening and signal attenuation caused by scattering and turbulence, which can greatly improve the performance of wireless UV communication system at low transmission power[4].

At this stage, there are many studies on channel estimation in various MIMO communication systems. The commonly used MIMO channel estimation methods and theories include minimum mean square error (*MMSE*) estimation[5], least square (LS) estimation[6], compressed sensing[7], Bayesian estimation[8], and multilayer perceptron (MLP) estimation[9], etc. For orthogonal frequency division multiplexing (OFDM) systems, a time-varying channel estimation method using two training symbols combined with polynomial fitting is proposed[10]. Diversity multiplexing technology is an important means to improve the performance of MIMO communication systems. The use of space diversity multiplexing technology[11] on NLOS UV links can reduce the fading caused by turbulence. There are also some researches on channel estimation for UV NLOS scattering communication[12,13], but they are limited to single-input single-output (SISO) systems. The problem of channel estimation in UV MIMO systems is still in the blank stage, and the applications of traditional nonlinear algorithms in UV communication have some defects, such as poor privacy, high complexity, and the need for prior channel characteristics, etc. To solve this problem, in this paper, deep learning technology is integrated into the UV MIMO communication system's channel estimation. Considering the sparseness of the two-dimensional channel state information (CSI) matrix in free space optical (FSO) communication[14], the MIMO channel estimation problem can be transformed into image processing. Deep learning has strong feature extraction and autonomous learning ability to obtain more complex channel characteristics[15]. Various neural network structures can be used as learning models to realize channel estimation of MIMO systems, including deep neural network (DNN)[16], convolutional neural network (CNN)[17], generative adversarial network (GAN)[18], and recurrent neural network (RNN)[19], etc. It is also an effective means to improve the accuracy of channel estimation by introducing neural network to improve the traditional channel estimation algorithms.

For the past few years, deep learning techniques have made some advancements in MIMO channel estimation. Several research results have been achieved, leading to improved performance compared to traditional channel

* This work has been supported by the National Natural Science Foundation of China (No.61971345), the Shaanxi Province Key R&D Program General Project (No.2021GY-044), the Technology Program of Yulin City (No.2019-145), and the Artificial Intelligence Key Laboratory of Sichuan Province (No.2022RYY01).

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estimation methods. For example, an autoencoder (CNNAE) classifier based on a CNN utilized for channel estimation is proposed, which have demonstrated superior performance compared to traditional methods[20]. Attention mechanism (AM) is a widely used technique in deep learning that enhances the performance of neural networks. By imitating the AM of the human brain, AM enables the model to concentrate on specific parts or features of the input data, thereby improving overall performance. For traditional massive MIMO systems, a novel attention-assisted deep learning channel estimation framework is proposed in 2022[21]. This framework effectively integrates AM into a fully connected neural network. The results demonstrate that the channel estimation performance is greatly enhanced with the assistance of the AM. In the same year, a CNN-based channel estimation method is proposed for millimeter-wave large-scale MIMO communication systems, simplifying the conventional estimation process[22]. In summary, introducing neural networks to enhance traditional channel estimation algorithms is an effective means of improving the accuracy of channel estimation. Promising results have been always shown by deep learning in various MIMO systems.

In this letter, deep learning is used to NLOS UV MIMO communication and a neural network-based wireless UV MIMO scattering channel estimation method is presented. We use the CNN to output a high-precision CSI matrix to extract the UV MIMO channel's statistical properties accurately, which serves as a foundation for future signal detection, thereby improving the performance of the communication system.

The study object is a uniformly distributed wireless UV MIMO communication system. Fig.1 shows the UV MIMO single scattering channel model composed of M transmitting antennas and N receiving antennas. (T_1, $T_2\ldots$, T_M) are M transmitting antennas, (R_1, $R_2\ldots$, R_N) are N receiving antennas, d is the communication distance, β_T and β_R are the transmitting elevation angle and receiving elevation angle respectively, θ_T is the beam divergence angle, θ_R is the field of view angle for the receiver, and ϕ_T and ϕ_R are the off-axis angles. The spacing between adjacent transmit antennas is u. The above-mentioned channel geometry parameters and atmospheric turbulence environment parameters jointly determine the channel characteristics.

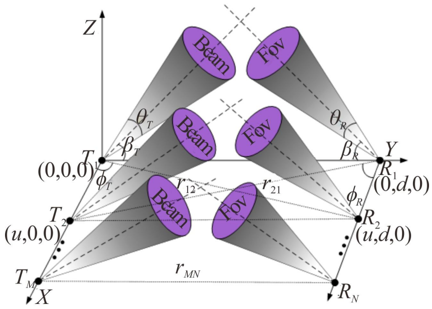


Fig.1 Wireless UV MIMO single scattering channel model

In the proposed scheme, we adopt the pulse position modulation (PPM) method with intensity modulation and direct detection (IM/DD) for the UV signal and assume that the transmitted beam is small enough. The correlation between the light signals received by the small aperture can be ignored. For the MIMO channel shown in Fig.1, the signal sent by the ith transmitter is denoted by x_i, the signal received by the jth receiver is denoted by y_j, and the channel response coefficient between the ith transmitter and the jth receiver is h_{ij}. The received signal expression is as follows

$$\boldsymbol{y}=\boldsymbol{Hx}+\boldsymbol{N}, \tag{1}$$

where $\boldsymbol{H}$ is the channel response matrix, and $\boldsymbol{N}$ denotes the additive white Gaussian noise (AWGN). For the $M\times N$ UV MIMO system, Eq.(1) can be expressed as

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix}=\begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1M} \\ h_{21} & h_{22} & \cdots & h_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ h_{N1} & h_{N2} & \ldots & h_{NM} \end{bmatrix}\cdot\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_M \end{bmatrix}+\begin{bmatrix} N_1 \\ N_2 \\ \vdots \\ N_N \end{bmatrix}. \tag{2}$$

Based on the investigation of the NLOS UV single-scattering channel[23], a simplified approximate expression for the channel impulse response has been derived, which is as follows

$$h_{ij}(t)=\frac{k_{\mathrm{s}}\theta_R\theta_T^2\sin(\beta_R+\beta_T)\exp(-k_{\mathrm{e}}ct)}{4\pi^3 r_{ij}\sin(\beta_T)(1-\cos\dfrac{\theta_T}{2})}, \tag{3}$$

where k_{s} is the scattering coefficient and k_{e} is the extinction coefficient, c is the lightspeed, and r_{ij} is the distance between the ith transmitter and the jth receiver.

Assuming that the channel state information between the transmitting end and the receiving end is known[24], the bit error rate (BER) of the MIMO communication system can be expressed as

$$P_{\mathrm{e}}=\int_{-\infty}^{\infty}N\left(-\frac{2\delta_x^2}{M+N},\frac{4\delta_x^2}{M+N}\right)Q\left(\frac{\eta I_0\mathrm{e}^x}{2\delta_v^2}\right)\mathrm{d}x, \tag{4}$$

where δ_x^2 and δ_v^2 are the power spectral densities of the UV transmission signal and AWGN, respectively. I_0 is the luminous intensity satisfying log-normal distribution. η is the photoelectric conversion efficiency of the UV detector. $N(\cdot,\cdot)$ is the Gaussian distribution function. $Q(\cdot)$ is the complementary cumulative distribution function, which is specifically expressed as

$$Q(x)=\int_x^{\infty}\frac{1}{\sqrt{2\pi}}\exp(-\frac{1}{2}t^2)\mathrm{d}t. \tag{5}$$

In addition to atmospheric scattering and absorption, the optical power attenuation that occurs after the UV signal is transmitted through the channel is also related to the scintillation attenuation (SA) caused by atmospheric turbulence. For the line-of-sight (LOS) link in the case of the plane wave, the SA caused by turbulence can be approximated by Rytov theory[25] as

$$\alpha=2\cdot\sqrt{23.17\cdot C_n^2\cdot(2\pi/\lambda)^{7/6}\cdot d^{11/6}}, \tag{6}$$

where C_n^2 is the refractive index structure parameter, which is used to measure the intensity of atmospheric turbulence. λ is the UV wavelength. d is the communication distance. Similar to the study of single scattering[23], the NLOS link is also regarded as the sum of two LOS links, d_1 is from the transmitter to the scattering volume and d_2 is from the scattering volume to the receiver, respectively.

In this paper, we use the logarithmic normal (LN) distribution model to describe the UV signal intensity distribution. To facilitate the calculation, the transmission signal intensity is normalized, and the probability density function can be expressed as[26]

$$f_{\mathrm{t}}(I/\langle I\rangle)=\frac{1}{\sqrt{2\pi\sigma_I^2}\left(I/\langle I\rangle\right)}\times \exp\left\{-\left[\ln\left(\frac{I}{\langle I\rangle}\right)+\sigma_I^2/2\right]^2\Big/2\sigma_I^2\right\}, \tag{7}$$

where I is the fluctuation of light intensity. $\langle\cdot\rangle$ is the average operation. σ_I^2 is the logarithmic intensity fluctuation variance of the transmitted optical signal, which can be expressed as

$$\sigma_I^2=\exp\left(4\sigma_X^2\right)-1, \tag{8}$$

where σ_X^2 is the variance of the logarithmic amplitude variable X, related to C_n^2 at different atmospheric altitudes h, specifically

$$\sigma_X^2=0.56\left(2\pi/\lambda\right)^{7/6}\int_0^d C_n^2(h)(d-h)^{5/6}\,\mathrm{d}h. \tag{9}$$

As the UV photons reach the receiving end after single scattering, the conditional probability density function of the received optical signal intensity is

$$f_{\mathrm{r}}(I_{\mathrm{r}}|I)=\frac{1}{\sqrt{2\pi}I_{\mathrm{r}}\sigma_{\mathrm{r}}}\exp\left\{-\left[\ln\frac{I_{\mathrm{r}}}{E\left(I_{\mathrm{r}}|I\right)}+\frac{1}{2}\sigma_{\mathrm{r}}^2\right]^2\Big/2\sigma_{\mathrm{r}}^2\right\}, \tag{10}$$

where σ_{r}^2 is the logarithmic intensity fluctuation variance of the received optical signal. According to the above derivation, the marginal probability density function of the received optical signal intensity can be obtained as

$$f_{\mathrm{r}}\left(I_{\mathrm{r}}\right)=\int f_{\mathrm{r}}(I_{\mathrm{r}}|I)f_{\mathrm{t}}\left(I\right)\mathrm{d}I. \tag{11}$$

The overall scheme of channel estimation of UV MIMO system based on CNN is shown in Fig.2. The transmission signal is sent out from multiple UV sources by space-time coding at the transmitting end and is received by multiple UV detectors of the receiving end after passing through the atmospheric channel. Firstly, the initial channel state information, ie, the channel response coefficient matrix, is estimated by the LS algorithm, but this result does not consider the influence of noise and co-frequency interference. Next, the initial estimation result is used as the input of the neural network to obtain high-precision channel state information. After the nonlinear mapping of the network, the final result is the channel state information enhanced by CNN.

The deep learning based UV channel estimation scheme in this paper is an optimization of the channel estimation module of the whole UV communication system. The final output of the network is the high accuracy CSI state information which is used to estimate and predict the original input signal before passing through the UV turbulent channel and then using this estimated signal to continue into the subsequent communication system module to complete the whole communication process.

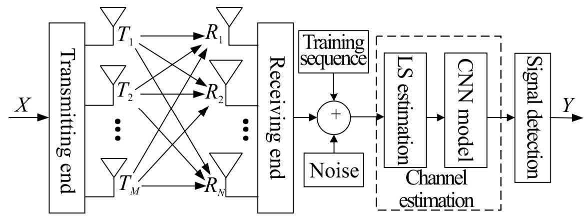


Fig.2 Channel estimation scheme of UV MIMO system based on neural network

The initial estimation of LS is carried out by using the random training sequence and received signal, and the result is a two-dimensional channel response coefficient matrix, which is converted into an image and used as the input of the neural network, as shown in Fig.3. The core of the CNN model designed in this scheme is a three-layer network, including a pooling layer and two convolutional layers. A high-precision CSI matrix is reconstructed through the CNN to eliminate noise and other interference items, thereby obtaining more accurate channel state information.

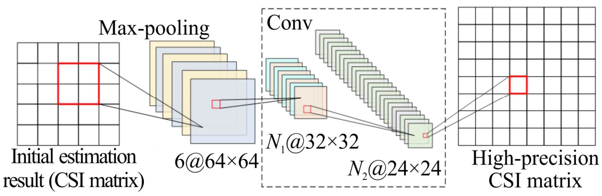


Fig.3 CNN model structure

In the designed CNN of this paper, the max-pooling method is utilized to reduce the model size and the data space occupied by the network. The size of the pooling window is set to 2×2, which reduces the input image to a quarter of its original size. The depth of the feature map in the pooling layer is set to 6. Two convolutional layers are set up for feature extraction and nonlinear mapping, respectively, as shown in Fig.3. The size of the convolution kernel is set to 3×3. The size of the feature map of the first step convolution is set to 32×32, which is divided into N_1 layers, and the size of the feature map of the second step convolution is set to 24×24, which is divided into N_2 layers. To speed up the convergence process, rectified linear unit (ReLU) is used as the activation function in all layers of the network, which is expressed as

$$\mathrm{ReLU}\left(x\right)=\max\left(x,0\right). \tag{12}$$

The deep learning methods employed in channel estimation in this paper fall under the class of regression prediction problems. Accordingly, the mean square error (*MSE*) function is chosen as the loss function, which is defined as follows

$$Loss=\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left\|\hat{h}_{ij}-h_{ij}\right\|_2^2, \tag{13}$$

where $\hat{h}_{ij}$ is the output predicted value of the network, h_{ij} is the target output, and $\|\cdot\|_2^2$ is the 2-norm operation.

The proposed AM-CNN channel estimation process mainly consists of three parts, namely the input layer, the network layer, and the output layer, as shown in Fig.4. The deep learning methods employed in channel estimation in this paper fall under the class of regression prediction problems. Accordingly, the *MSE* function is chosen as the loss function, which is defined as follows. The input layer mainly needs to model the UV MIMO channel, and then generate the sample data set of channel characteristics and training sequences. The LS algorithm is used to estimate the initial CSI matrix as the input of the network layer. The task of the output layer is to reconstruct the high-precision channel estimation result through CNN. The training process of CNN is to calculate the loss error between the target information in the input layer and the final result of the output layer, and use the Adma algorithm to iteratively optimize the model, which can adaptively update the parameters.

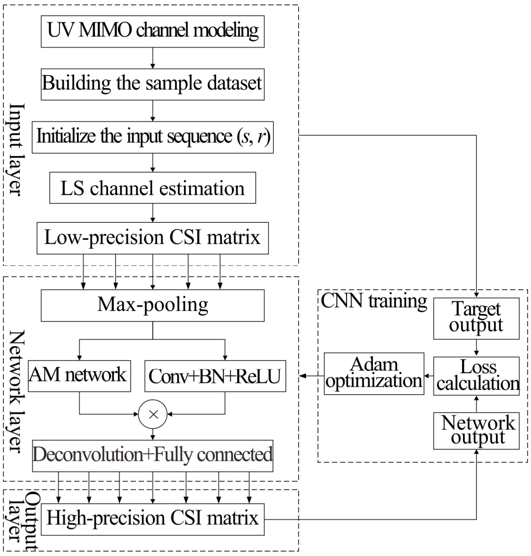


Fig.4 AM-CNN channel estimation flow chart

To improve the feature extraction ability and accuracy of the network layer, the AM is applied to the construction of CNN[27]. AM achieves selective processing of input data by assigning weights to different elements of the input data. These weights reflect the importance of each input element to the output, allowing the model to selectively rely on the contributions of various elements. By assigning weights, the AM makes the model adaptively focus on parts of the input data that have different importance. The shallow features extracted by CNN are input into AM network, and then further fused with the features extracted by convolution (Conv) and batch normalization (BN) to obtain deep features. Finally, the deep features are noise filtered by the deconvolution operation, and then output through the fully connected layer. The AM operation process is mainly divided into three stages, and the specific steps are as follows.

Step 1: The initial CSI matrix extracted from the convolutional layer is composed of a series of (h, key), and given a target element $h_{i,j}(0\le i\le M, 0\le j\le N)$, where M and N represent the dimensions of the MIMO antenna matrix. In the attention layer, the similarity between $h_{i,j}$ and each key_t ($0\le t\le MN$) is calculated by performing the inner product operation of two vectors, and the expression is

$$\text{similarity}\left(h_{i,j},key_t\right)=h_{i,j}\cdot key_t. \tag{14}$$

Step 2: To deal with the inconsistency of the value range of the numerical results generated in Step 1, the SoftMax function is used for numerical conversion and normalization. The operation is as follows

$$a_t=\text{SoftMax}\left(Sim_t\right)=\frac{\mathrm{e}^{Sim_t}}{\sum_{p=1}^{MN}\mathrm{e}^{Sim_t}}. \tag{15}$$

Step 3: Calculate the corresponding weight coefficient when a_t is h_t, and then weighted sum to obtain the attention value. The expression is

$$\text{Attention}\left(a_t,h_t\right)=\sum_{t=1}^{MN}a_t\cdot h_t. \tag{16}$$

To verify the effect of the channel estimation scheme proposed in this paper, we conduct simulation experiments on the UV MIMO channel model and the AM-CNN channel estimation method by MATLAB and Python. The basic simulation parameters of the UV MIMO communication system are set as follows, λ=255 nm, area of receiving aperture is A_r=1.77 cm^2, (k_s, k_e)=(0.74, 0.49) km^{-1}, the emitted pulse power is P_t=100 mW, communication rate is R_b=1 Mbit/s, (θ_T, θ_R)=(15°, 15°), and the separation distance between adjacent transmitting antennas is u=5 m. Taking the 3×3 MIMO channel as an example, we analyze the correlation characteristics of the scattering channel. For the 3×3 channel response matrix, according to the positions of different transmitting and receiving antennas, h_{11}, h_{22}, h_{33} are coplanar, and h_{12}, h_{21}, h_{23}, h_{32}, h_{13}, h_{31} are noncoplanar. Different communication distances d will cause the channel response coefficients to change, as shown in Fig.5. Under the same position condition, the pulse broadening will become larger with the increase of d. When the position conditions are different, the channel response amplitude under noncoplanar condition is lower than that under coplanar condition, and the pulse broadening becomes larger, because the existence of off-axis angles will lead to more serious scattering attenuation.

For the weak turbulence environment, the turbulence intensity is fixed, i.e., $C_n^2=10^{-16}\,\mathrm{m}^{-2/3}$. Fig.6 shows the probability density function (PDF) of the optical signal intensity under different communication distances and elevation angles. It can be seen from Fig.6 that with the increase of the communication distance and elevation angles, the variance of the received optical signal PDF intensity gradually increases, that is, the signal energy attenuation increases accordingly.

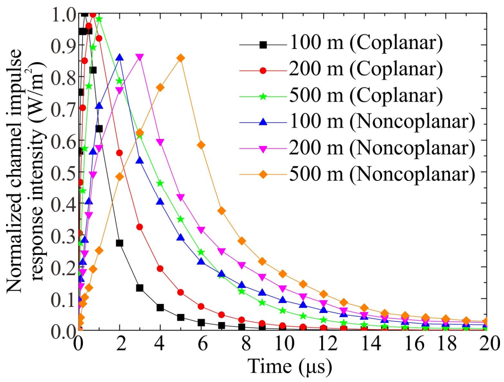
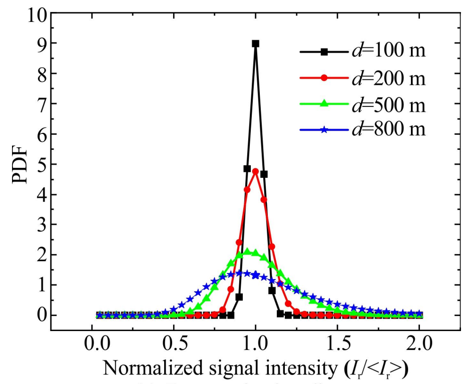
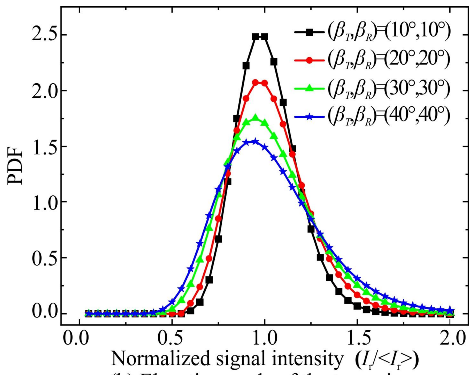


Fig.5 Channel impulse responses at different communication distances



(a) Communication distance



(b) Elevation angle of the tansceiver

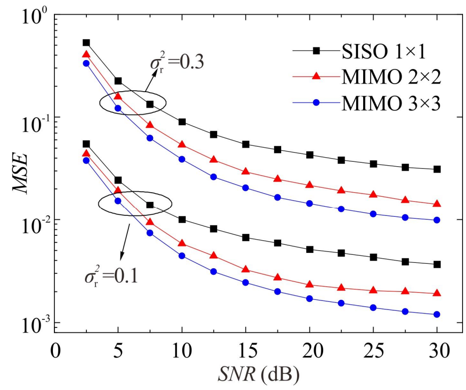
Fig.6 PDF curves of the received optical signal intensity under different parameters

Based on a 3×3 UV MIMO communication system, the neural network training data set is constructed according to the above channel characteristics. Taking *MSE* and *BER* as the measurement standard, the performance of the AM-CNN estimation method is simulated. The relevant settings of the neural network in this scheme are shown in Tab.1.

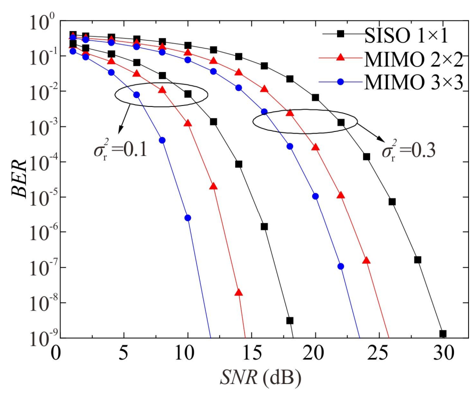
According to the above simulation results of channel characteristics, the selected channel parameters are d=100 m, β_T=β_R=10°, $C_n^2=10^{-16}\,\mathrm{m}^{-2/3}$. The influence of different MIMO structures on the channel estimation performance of AM-CNN under two scintillation variances σ_r^2 is analyzed, as shown in Fig.7. It can be seen from Fig.7 that with the increase of the number of transmitting and receiving antennas, the *MSE* and *BER* gradually decrease, and the performance of *MSE* and *BER* under MIMO is greatly improved compared with SISO. Besides, when the σ_r^2 becomes larger, the performances of *MSE* and *BER* become worse. Therefore, for UV MIMO communication systems, the proposed scheme can effectively suppress the channel attenuation caused by scattering and turbulence effects.

Tab.1 The proposed neural network hyperparameter settings

Parameter	Value
Dropout	0.6
Learning-rate	0.01
Mini-batch size	10
Data size	3 000
Dataset split (train: test)	7: 3
N_1 (Convolution layer)	7
N_2 (Convolution layer)	5



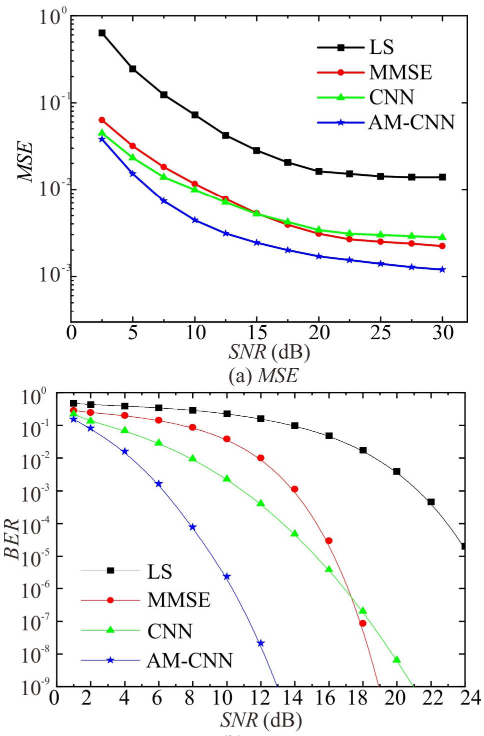
(a) *MSE*



(b) *BER*

Fig.7 Channel estimation performance of different MIMO structures

A performance comparison and analysis of various channel estimation schemes by calculating the *MSE* and *BER* under different signal-to-noise ratios (*SNRs*) is presented in Fig.8. Fig.8(a) shows that the *MSE* decreases with the increase of the *SNR* as a whole, that is, the estimation performance continues to improve. The *MSE* performance of AM-CNN proposed in this paper is significantly improved compared to the LS estimation. The performance of the traditional CNN model without introducing the AM can only approximate the *MMSE* estimation, and the AM-CNN can obtain better *MSE* performance than the *MMSE* estimation after introducing the AM. Fig.8(b) shows that the *BER* curves of four channel estimation schemes decrease gradually as the *SNR* increases, and compared with the other three channel estimation methods, AM-CNN estimation has better *BER* performance.



(b) *BER*

Fig.8 Channel estimation performance curves with different methods

In conclusion, we use the CNN and AM to realize channel estimation in UV signal processing. It was experimentally confirmed that the proposed scheme can achieve better channel estimation effect under the UV MIMO structures with different numbers of transmitting and receiving antennas, and the performance of AM-CNN estimation is significantly improved compared with the traditional channel estimation methods of LS and *MMSE*. Indeed, the deep learning channel estimator proposed in this paper demonstrates its suitability for handling signal processing in wireless UV MIMO communication systems. In future work, the reliability of multi-scattering MIMO channel transmission in mobile scenarios will be the focus of our research.

Ethics declarations

Conflicts of interest

The authors declare no conflict of interest.

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