mmWave Channel Estimation in UAV Enabled Communication Network

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Unmanned aerial vehicles (UAVs) are revolutionizing telecommunication networks by offering innovative solutions to bridge coverage gaps and extend connectivity. However, to ensure reliable and efficient communication between UAVs and ground stations, accurate channel estimation becomes a critical factor. Therefore, much research has been presented in the field of millimeter wave channel estimation. Although, it is necessary to investigate the role of UAVs as a relay between terrestrial users and satellite networks. In this regard, an estimating channel method is proposed. First, due to the noise removal ability of the autoencoder network, it is used to reduce the received signal noise. Next, channel coefficients are estimated with the help of a designed CNN network. Finally, the combining matrices used at the receiver are updated to improve the SNR. The simulation results show that the designed neural networks for noise removal and channel estimation improve the accuracy. Also, updating the combining matrices at the receiver shrinks the area to scan and consequently more directed beams can be used that improve the SNR. Using the proposed structure, the overall accuracy can be improved around 10% for different SNRs.

Keywords: Unmanned Aerial Vehicles, mmWave Channel Estimation, Autoencoder, CNN.

1. Introduction

In recent years, the rapid development of UAVs, commonly known as drones, has paved the way for their utilization across various industries [1]. One domain where UAVs have shown immense promise is in telecommunication networks. These flying devices are revolutionizing the way we think about connectivity by providing innovative solutions to address coverage gaps, disaster response, and network maintenance. Some of the most important roles of UAVs in telecommunication networks are extending coverage and connectivity, rapid deployment in emergency situations, network maintenance and inspection, and surveillance and security [2]:

Channel estimation in UAV-enabled telecommunication networks is of utmost importance as it determines the quality of the received signal and enables efficient modulation and demodulation techniques. Accurate channel estimation is crucial for optimal resource allocation, effective power control, and robust error correction, all essential for reliable and high-performance communication in UAV-enabled telecommunication networks. However, channel estimation for UAVs presents unique challenges due to their mobility, altitude variations, and dynamic environments. These challenges necessitate the development of specialized techniques to overcome them. Traditional methods, like pilot-based estimation, are commonly used, but advanced techniques, including machine learning algorithms and advanced signal processing, are being explored to address the specific needs of UAV communication systems [3]. The future holds opportunities for further advancements, such as integrating artificial intelligence, MIMO techniques, and beamforming algorithms, to improve the accuracy and reliability of channel estimation in UAV networks.

Numerous studies have been conducted on UAV mmWave channel estimation; a selection of the most significant ones is presented [4-8]. In [9] a new approach called Adaptive-Structure Extreme Learning Machine (ASELM) presented that enables fast channel prediction for obtaining Channel State Information (CSI) in a proactive manner. This method facilitates agile beam-based inter-UAV while maintaining prediction accuracy at reasonable costs. [10] introduces an innovative approach to spatial beam training, considering the three-dimensional (3D) space in which UAVs operate.

[11] This paper introduces a novel framework for performing data-driven air-to-ground channel estimation in millimeter-wave (mmWave) communications within a wireless network of unmanned aerial vehicles (UAVs). The framework addresses the need for accurate channel information in mmWave communication by developing an effective channel estimation approach. This approach enables each UAV to collect mmWave channel data and train an independent channel model using a conditional generative adversarial network (CGAN) along each beamforming direction. [12]

[13] focuses on addressing the challenge of channel estimation in a multi-user system using unmanned aerial vehicles (UAVs) and operating in the millimeter-wave (mmWave) frequency range. The specific challenges addressed are the beam squint effect, which occurs in mmWave massive multiple-input multiple-output (MIMO) systems, and the time-varying nature of the channels caused by the mobility of the UAVs. [14] proposed a method to simultaneously estimate the position of the unmanned aerial vehicle (UAV) and it presented a matrix completion approach to recover the performance.

In [15], a new autoregressive (AR)-Gaussian channel prior is introduced to effectively represent the sparsity and clustering characteristics of mmWave MIMO Internet of Things (IoT) channels. Subsequently, a channel approximation technique is presented to address the challenges posed by channel uncertainty. This method leverages the inherent structure of the AR-Gaussian channel prior to provide an accurate estimation of the channel. [16] developed a model for the mmWave channel in a UAV-assisted scenario, incorporating hybrid beamforming and accounting for the effects of UAV jitter. By considering the random fluctuations in the UAV's attitude angle, authors determined the distribution of the angle of arrivals/departures (AOAs/AODs) in the channel.

[17] focuses on a millimeter-wave communication system that utilizes movable UAV based base stations. These UAV-base stations are equipped with antennas and multiple sensors to track the channels. To achieve an omnidirectional beam, a cylindrical array antenna is mounted on the movable UAV-base stations. Additionally, the article proposes the use of a deep neural network-based attitude estimation method as an alternative to traditional methods of attitude estimation. [18] introduces a new technique for predicting channel behavior during link blockages in the 28 GHz frequency band. Their method involves organizing multipath components (MPCs) along a UAV's flight path into separate path bins based on the minimum Euclidean distance among their channel parameters. Once organized, the channel parameters of the MPCs within each path bin are forecasted during periods of blockage.

Despite the fact that many researches have been presented in the field of channel estimation, it is necessary to consider the ability of autoencoder in noise removal and mmWave channel sparseness in the channel estimation process. Therefore, in the following, the system model is presented along with the proposed method.

2. System model

As depicted in Fig 1(a), a network of UAVs can be placed as a relay between users and the satellite network. With the help of these UAVs, the link quality for millimeter wave communication is improved and it provides the possibility of connecting users to the satellite at a high rate. The UAV is equipped with a uniform planar array (UPA) consisting of M_x antennas in the horizontal direction (X-direction) and M_y antennas in the vertical direction (Y-direction) (Fig1(b)).

Assuming there are U devices (Fig1(b)), the received pilots $Y[m]\epsilon C^{N\times T}$ during the mth measurements at the BS can be represented as stated in reference [14].

$$\mathbf{Y}[m] = \mathbf{F}_{\mathrm{BB}}^{H}[m]\mathbf{F}_{\mathrm{RF}}^{H}[m]\sum_{u=0}^{U-1}\mathbf{h}_u\mathbf{x}_u[m]^H + \mathbf{W}[m] \tag{1}$$

where $\mathbf{F}_{\mathrm{BB}}[m] \in \mathrm{C}^{N\times N}$ and $\mathbf{F}_{RF}[m] \in \mathrm{C}^{M\times N}$ shows the digital and the analog respectively regarding beamformers of the N-RF-chain HBF ($N \ll M$).

To stop pilot contamination, orthogonal pilots are allocated to each UE device, i.e $\mathbf{x}_u[m]^H\mathbf{x}_u[m] = T$ and $\mathbf{x}_u[m]^H\mathbf{x}_v[m] = 0$, and it assumed $T \gg W$. By multiplying $\boldsymbol{Y}[m]$ by $(1/T)\mathbf{x}_u[m]$ in 1 and defining $\boldsymbol{F}_{HBF}[m] \triangleq \boldsymbol{F}_{RF}[m] \times \boldsymbol{F}_{BB}[m]$, the measurement for the uth UE can be expressed as follows:

$$\tilde{\mathbf{y}}_u[m] = \mathbf{F}_{\mathrm{HBF}}^{H}[m]\mathbf{h}_u + \tilde{\mathbf{w}}_u[m] \tag{2}$$

Where $\tilde{\mathbf{w}}[m] \triangleq (1/T)\mathbf{W}[m]\mathbf{x}_u[m]^*$. It can be simplified as:

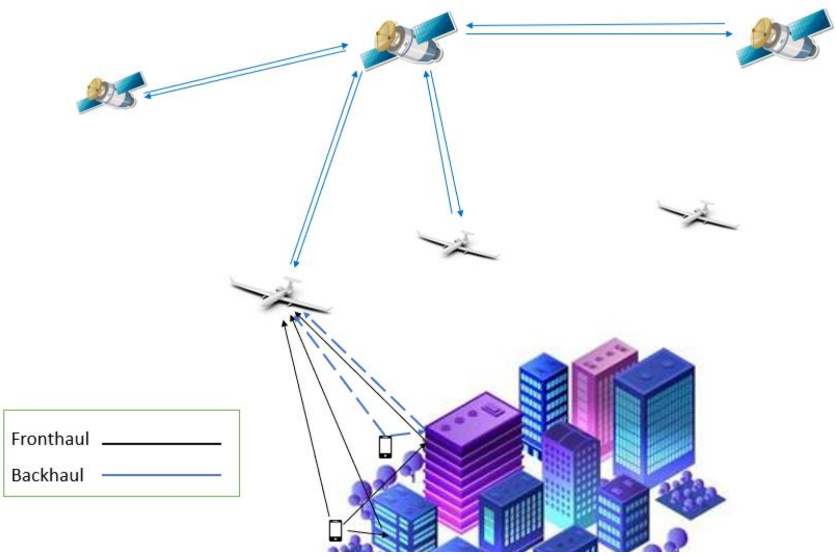
$$\tilde{\mathbf{y}}[m] = \mathbf{F}_{\mathrm{HBF}}^{H}[m]\mathbf{h}_u + \tilde{\mathbf{w}}[m] \tag{3}$$

and the channel response vector h can be generally given as [15]:

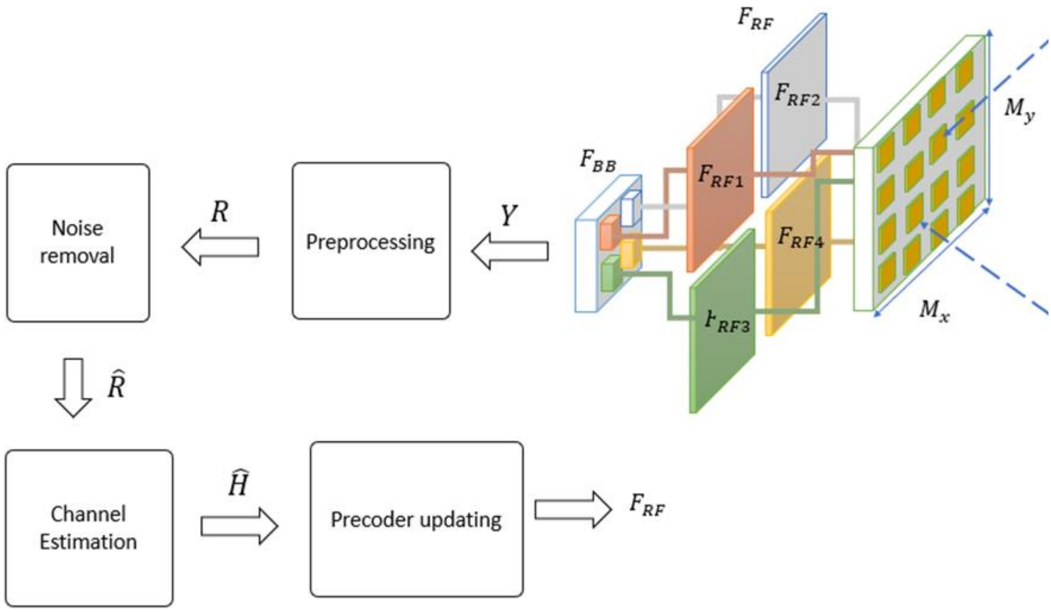
$$\mathbf{h} = \sum_{l=0}^{L-1}\sum_{p=0}^{P_l-1}\alpha_{l,p}\mathbf{a}_{\mathrm{Y}}\left(\mu_{l,p}\right)\otimes\mathbf{a}_{\mathrm{X}}\left(\mu_{l,p},v_{l,p}\right) \tag{4}$$

$$\begin{aligned}\left[\mathbf{a}_{\mathrm{X}}(\mu,v)\right]_{m_x} &= \frac{1}{\sqrt{M_x}}e^{-j2\pi\frac{d_x}{\kappa}(m_x-1)\sin\mu\cos v}\\ [\mathbf{a}\mathrm{Y}(\mu)]_{m_y} &= \frac{1}{\sqrt{M_y}}e^{-j2\pi\frac{d_y}{k}(m_y-1)\cos\mu}\end{aligned} \tag{5}$$

as $m_x = 1,\ldots, M_x$ and $m_y = 1,\ldots, M_y$. d_x and $d_y$represent the space of two adjacent antenna elements in X -direction and Y-direction, respectively. κ is the carrier wavelength.



(a)



(b)

Fig1: System model (a) and receiver structure along with processing steps (b) in mmWave UAV link

2.1 Channel estimation using deep learning

The general structure of the proposed method is shown in Fig1(b). The first part consists of a receiver structure UAV equipped with a hybrid UPA to improve SNR and support multiple users. After applying analog and digital combination matrices, the received signal is pre-processed by applying Z filters. In this case, the received signal will be a combination of channel and noise.

Then the noise is estimated and removed with the help of ENCODER neural network. Next, in the channel estimation section, the channel coefficients are estimated with the help of the designed neural network. Since the range of entry coefficients depends on the user's position, it is possible to update combining matrices in order to steer the beams toward the expected scatters. The detailed of each block is described below.

2.1.1 Preprocessing

In this section, a filter can be defined as follows to remove the effect of the combination matrix and access the channel information.

$$R = \boldsymbol{Z} \times \tilde{\mathbf{y}}[m] = \boldsymbol{Z} \times (\mathbf{F}_{\mathrm{HBF}}^{H}[m]\mathbf{h}_u + \tilde{\mathbf{w}}[m]) = \mathbf{h}_u + inv(\mathbf{F}_{\mathrm{HBF}}^{H}[m]) \times \tilde{\mathbf{w}}[m] = \mathbf{h}_u + \mathbf{w}'[m]$$

$$where \qquad (6)$$

$$\boldsymbol{Z} = inv(\mathbf{F}_{\mathrm{HBF}}^{H}[m])$$

In order to remove noise, Autoencoder networks can be used, which have a high ability to identify the noise pattern and remove it [19-23]. For this purpose, the structure shown in Figure 2 is designed. The input part of this network receives channel data for a specified number of frames and the real and imaginary parts are separated and create a 2D image. To start the reverse process, the fully connected (FC) layer computes the class scores, resulting in volume of size [1x1x576].

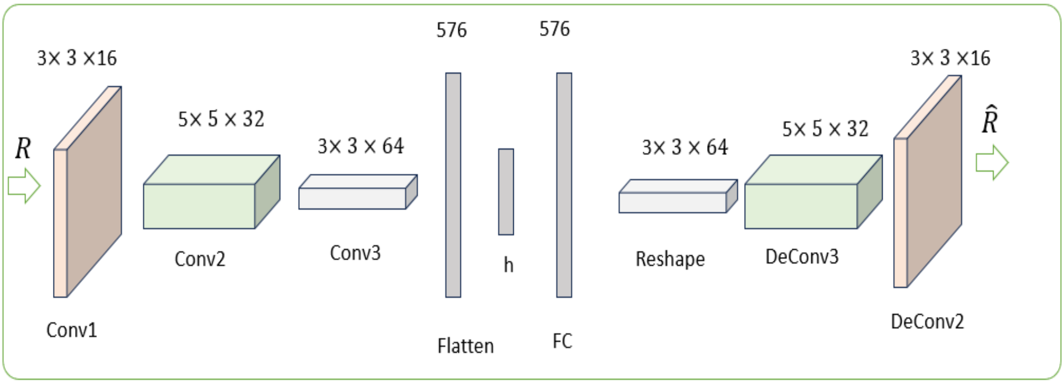


Fig2: Autoencoder structure for noise removal

2.1.2 Channel Estimation

After removing the noise, the channel data can be fed to another neural network which is shown in the Fig3, in order to improve the estimation. Since the channel values are complex, the real and imaginary parts are separated and fed to the network as a two-layer picture. The first layer is a convolution layer with the size of $3 \times 3 \times 32$ that uses 32 different 3 by 3 filters to the input image of size $M_x \times M_y \times 2$. Then the Relu layer which is a type of activation function to introduce non-linearity into the model is added. For other convolution layers a batch normalization (BN) is employed.

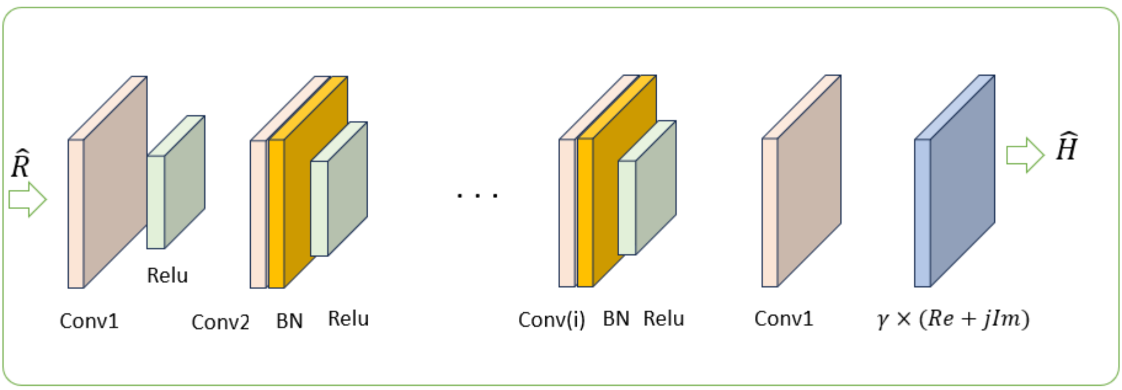
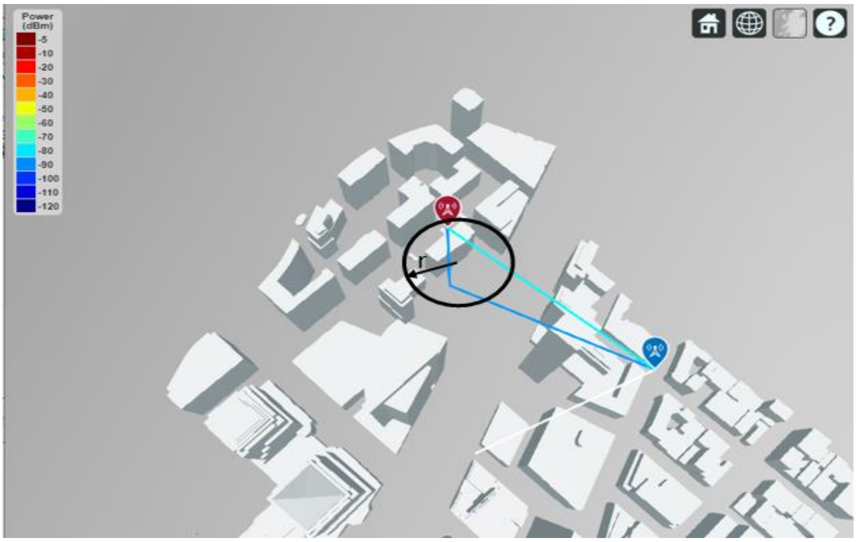


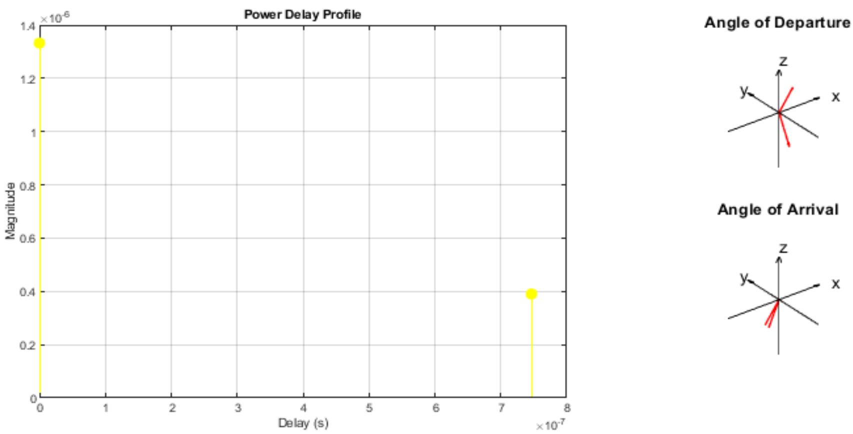
Fig3: CNN structure for channel estimation

2.1.3 Precoder Updating

Fig4 (a) shows the transmitter and the receiver channel paths, while Fig4 (b) shows the power delay profile, AoA, and AoD for this scenario. As it is shown the variance of AoA is small and can be considered in the channel estimation process. Besides, the matrices used for combining in the analog part of the receiver are first randomly selected with specific values to be able to receive information from different angles. Therefore, it is necessary to update combining matrices in each time slot in order to steer the combining beams toward the user. For this purpose, a circle with particular radius (r) is considered as it is shown in Fig4(a) and the m training frames are chosen from a set that are steering toward the angles inside the circle.



(a)



(b)

Fig4: The channel paths between the transmitter and receiver (a) and the power delay profile and AoA and AoD (b) for this scenario.

2.2 Loss Functions

In order to train the designed networks, it is necessary to define the loss functions for each of the networks separately. Therefore, different loss functions are defined for the noise removal network and the channel estimation network as follows:

$$\mathrm{L}_{\mathrm{CNN}_{noise\_removal}} = \sum_{i=1}^{M_x M_y} \left(\hat{R}_i^m - R_i^m\right)^2 \qquad (7)$$

$$\mathrm{L}_{\mathrm{CNN}_{Channel\_estimation}} = \sum_{i=1}^{M_x M_y} \left(\hat{H}_i^m - H_i^m\right)^2 \qquad (8)$$

$$\mathrm{L} = \mathrm{L}_{\mathrm{CNN}_{noise\_removal}} + \mathrm{L}_{\mathrm{CNN}_{Channel\_estimation}} \qquad (9)$$

Then the total loss function is L as defined in 9.

3. SIMULATION RESULTS

In this section, in order to evaluate the performance of the proposed method, the following model has been implemented in MATLAB software. For this purpose, the UPA structure is equipped with 32x16 antennas and 4x4 RF chain. It is assumed that the UAV receives the signal from4 paths in the mmWave channel with Gaussian noise as $n : N(0,\sigma^2)$ and the AoA is defined from $[0, \pi]$ randomly.

The performance criterion is based on the normalized mean squared error (NMSE) that is $NMSE = \frac{\sum_{d=0}^{N_c-1} \| \breve{H}_d - H_d \|_F^2}{\sum_{d=0}^{N_c-1} \| H_d \|_F^2}$.

Fig5 shows the channel estimation results for different SNRs. As shown, using the proposed method can achieve higher accuracy than the OMP [17] and hybrid [18] methods. In [17] the problem is solved by the OMP algorithm which makes use of a redundant dictionary comprising array response vectors characterized by finely quantized angle grids. While in [18], a hybrid channel estimation technique is employed, comprising two distinct stages. In the first stage, Compressed Sensing (CS) is utilized for channel estimation in the e-angles, taking into account their unique distribution characteristics. Subsequently, in the second stage, Sparse Bayesian Learning (SBL) is employed for channel estimation in the a-angles, which exhibit different distribution characteristics.

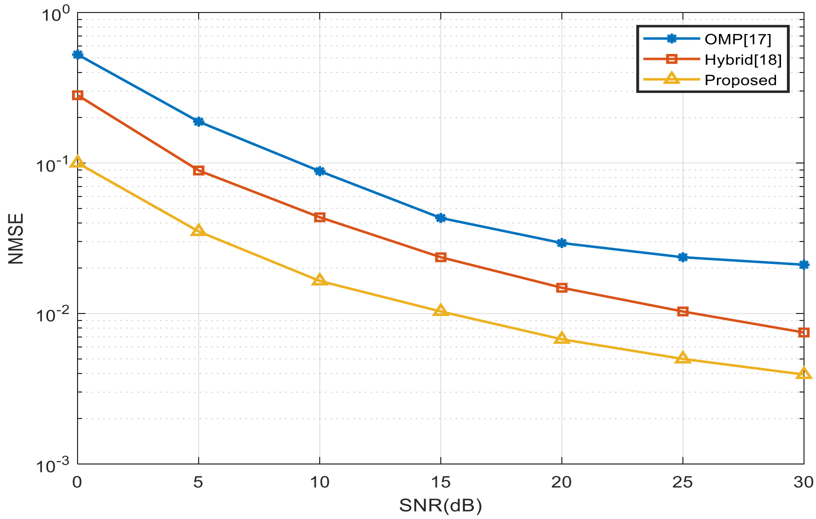


Fig5: Channel estimation results for different SNRs

Fig6 shows the channel estimation for different number of training frames. By increasing the number of transmitted frames, the accuracy of noise removal and channel estimation increases, but it reduces the resources for data in the coherence time of the channel. For any channel the coherence time is limitted and is used both for training frame and data. So, it is important to keep most of available for data transmission.

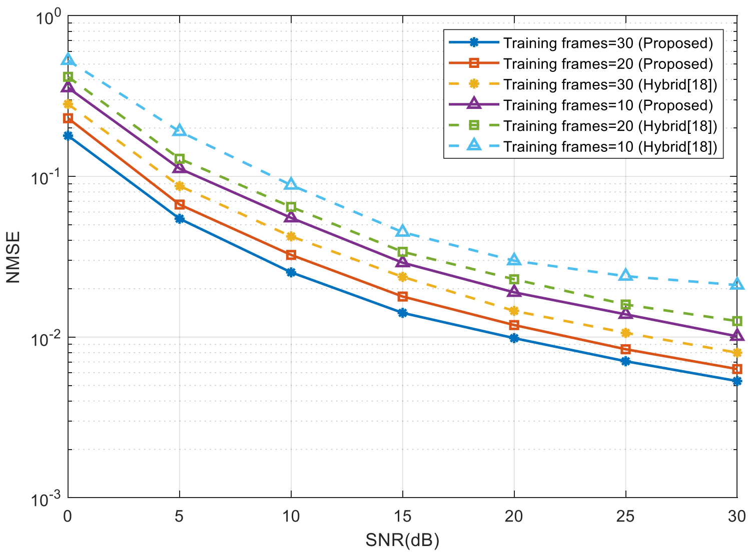


Fig6: Channel estimation results for different number of training frames

The simulation results show that the accuracy of channel estimation can be increased with the help of the presented framework. Removing noise, using the CNN for channel estimation, and limiting the transmitted beams due to the available information from the angle of arrival in previous time frames provides high accuracy.

4. Discussion

In order to estimate the millimeter wave channel, artificial neural networks were used. These networks excel in their ability to discern data patterns, making them suitable for distinguishing the desired signal from noise. In the provided framework, these networks were applied to eliminate noise and calculate channel coefficients, resulting in notably high precision. Furthermore, considering the sparse nature of millimeter wave channels, a technique is introduced to enhance channel estimation accuracy by updating the combining matrices at the receiver. This update process effectively improved the SNR. Additionally, assessments demonstrated that employing higher SNRs during network training yielded improved accuracy, as the networks could more effectively capture data patterns.

5. Conclusion

In this paper, a channel estimation method for UAV-enabled link is proposed, which consists of three stages. In the first step, using the designed autoencoder network, the noise pattern in the received data is estimated and removed. Then, in the second step, the channel coefficients are estimated with the help of the designed neural network. Finally, with the help of the received angles in the current time interval, the range of angles is estimated and the composition matrices are updated in such a way that they only have bias in these directions. The use of these matrices increases the final accuracy of the method. Also, the results show that the use of neural networks in different channel conditions can provide better accuracy.

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