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Channel estimation for rician fading with attention mechanism

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Abstract. The outdoor terahertz communication channel imposes challenging constraints in the sixth generation (6G), which has attracted researchers to investigate this piece of spectrum band 0.3-10 Thz. In this paper, we deploy a new transformer architecture called HA02 to attain enhanced channel estimation in Orthogonal Frequency-Division Multiplexing (OFDM) systems. This method is based on the self-attention mechanism which focuses on the most important elements of the Least–Squares (LS) method, it utilizes a transformer encoder block as the encoder and a residual neural network as the decoder. Using the Rician channel model while considering the presence of Free Space Path Loss (FSPL) and the influence of weather conditions on the Thz link's performance. Our simulations demonstrate high estimation performance compared with some channel estimation techniques.

1 Introduction

Nowadays, the extensive demand for industrial applications in terms of reliability and high data rates has made the 5G mobile networks unable to meet the wireless communication services requirements. Hence, the 6G wireless technologies have come up with advanced performances (up to 1 Tbps as Maximum data rates and 99.9999999% as reliability) [1], capable of overcoming the limitations of current 5G networks. Artificial intelligence (AI) is paramount in 6G to achieve these ambitious KPIs. It has solved many communication systems problems, particularly channel estimation issues in orthogonal frequency-division multiplexing (OFDM) systems. Due to the variation characteristics of the wireless channel, it cannot be precisely modeled. Nevertheless, the integration of AI has shown a great improvement in recovering transmitted symbols.

Mobile wireless communication is gravely affected by interference resulting from reflections, which involves performance degradation in terms of bit error rate (BER) and throughput. So, the system needs an accurate estimate of the propagation channel. Many methods have been proposed and optimized to mitigate this problem, such as least squares (LS) and minimum mean-square error (MMSE) [2]. However, the first approach doesn't give an accurate channel estimation and the second one demands precise channel statistics in advance. This leads to many machine-learning solutions for estimating the wireless channel. In [3], the authors proposed a framework called channelNet, which is one of the first deep neural network models used for channel estimation. They consider the channel as an image that is known only at the pilot positions, by concatenating two CNN-based (Convolutional Neural Network) algorithms, super-resolution network (SRCNN) [4] and denosing neural network (DnCNN) [5], the unknown values of the channel response are founded. The paper [6] also deployed ChannelNet but proposed a mechanism for finding good pilot positions, allowing high channel estimation accuracy. Residual channel Estimation Network (ReEsNet) [7], a residual learning-based neural network, is applied to estimate the channel for the OFDM system with a smaller number of learned parameters. The paper [8] has presented a neural network solution for channel estimation named Interpolation-ResNet which can attain an enhanced performance for any pilot pattern in the downlink scenario with generalization capability for different channel models described in the 3GPP documents.

As Large Language Models (LLMs) have revolutionized several fields, the telecom domain has also been influenced. Indeed, numerous efforts have been devoted to improving the channel estimation accuracy using the transformer [9], which is a model architecture relying on an attention mechanism. This later has made important progress in the study of wireless transmission. The paper [10] has used a channel estimation method based on deep learning and CNN combined with transformer architecture, giving higher estimation robustness under a highly dynamic environment with 6dB higher than LMMSE. In [11], it has been proposed for the first time an encoder-decoder architecture based on a self-attention mechanism called HA02 (Hybrid architecture), applied in a 5G New Radio (NR) environment using 3GPP channel models by treating just a single-input-single-output (SISO) and Rayleigh fading scenario.

This paper proposes using the Hybrid transformer architecture to estimate the rician fading channel in the Ter-

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ahertz (THz) band of wireless communication. This later consists of two blocks, the encoder part is based on [9], and the decoder is a residual neural network. Through processing the transformer input, which is the LS estimation in pilot positions, the focus will be on the principal elements among the LS estimate. From the simulation results, HA02 presents a high performance compared to the LS method and transformer Architecture for a Rician Thz wireless communication link including the joint influence of the weather effects and the inescapable FSPL.

The remainder of this paper is organized as follows: Section II introduces the rician Thz system and channel model simulating the 6G mobile network environment. Section III describes the Hybrid architecture based on the attention mechanism applied in the THz fading. Section IV presents simulation results. Lastly, conclusions are drawn in Section V.

2 System architecture

2.1 Channel Model

In the radio mobile systems, the Base Station (BS) is generally well above city buildings with no major scatterers nearby, while the Mobile Station (MS) is often immersed in a complex scattering environment. As shown in Fig.1, the transmitted signal takes multiple paths to arrive at the receiver due to reflections, diffraction, and scattering of the signal off objects and buildings in the environment. Consequently, the received signal is time-varying and may be highly attenuated. To model the wireless channel between

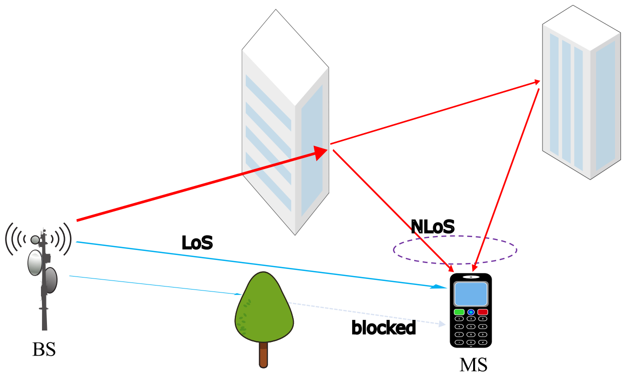

Figure 1. Multipath chammel.

the BS and MS, it is supposed to be a broadband wireless channel with a line of sight (LOS) component, the impulse response $h(t, \tau)$ is Rician fading given by [12]:

$$h(t,\tau) = \frac{1}{\sqrt{1+K}} h_{NLOS}(t,\tau) + \sqrt{\frac{K}{1+K}} h_{LOS}(t)\delta(\tau) \quad (1)$$

where K is the Rice factor, h_{NLOS} and h_{LOS} being Rayleigh fading and the LOS component with normalized unit energy, respectively. The received signal in the time domain $y(n)$ is expressed as:

$$y(t) = h(t) * x(t) + w(t) \quad (2)$$

Where $*$ symbolizes the convolution operation, $w(t)$ represents the Additive White Gaussian Noise (AWGN), and $x(t)$ is the transmitted signal.

2.2 Analysis of Thz link

In addition to the Rican fading, the Thz link under study is assumed to include the total attenuation modeled by the factor h_l, which can be written as

$$h_l = h_{fl} h_{wl} \quad (3)$$

where h_{fl} represents the free space path loss described by Friis's equation [13]

$$h_{fl} = \frac{c}{4\pi f z} \quad (4)$$

with c being the light's speed, f being the Thz carrier frequency , z standing for the distance between transmitter and receiver.
And h_{wl} is the weather effects attenuation expressed as

$$h_{wl} = \exp(-a_w z) \quad (5)$$

$a_w(Km^{-1})$ denotes the experimental attenuation coefficient due to the weather effect.

3 Hybrid transformer architecture for channel estimation in Thz band

The system under study is depicted in Fig.2, representing the wireless communication block diagram. After the modulation of the bit stream using 16-QAM, the generated symbols are converted from serial to parallel after that pilot signals are inserted. The Inverse fast Fourier Transform (IFFT) changes the frequency domain data symbols to the time domain OFDM signal samples. Each slot consists of $N_s = 28$ OFDM symbols and each OFDM symbol contains $N_f = 128$ subcarriers.The 1^{st}, 7^{th}, 21^{st}, 27^{th} OFDM symbols are reserved for pilots ($N_{pilot} = 4$). Fig. 3 represents the pipeline of the chosen pilot positions approach at the frequency domain schematized by a black square. For all Pilot OFDM symbols, the pilot subcarriers are spaced by 2 subcarriers, however for 1^{st} and 21^{th} OFDM symbols, their indices start from the first subcarrier and others from the second pilot subcarrier. We consider a Rician fading

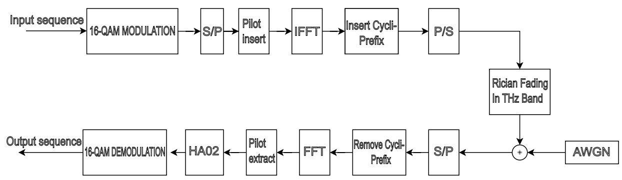

Figure 2. Block diagram of wireless channel including hybrid transformer architecture (HA02).

scenario including the total attenuation coefficient given in (1) with an additive white Gaussian noise.

On the receiver side, the inverse operations executed at the transmitter are applied to the received signal. After

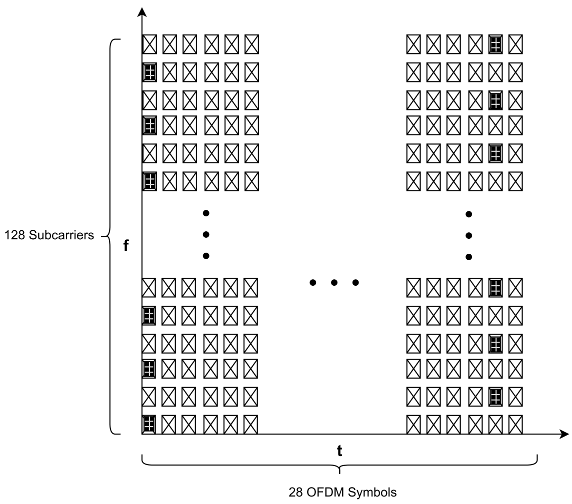

Figure 3. Pilot positions at the transmitted frame.

extracting pilot symbols, the frequency domain LS estimation is calculated by

$$\hat{H}_{LS} = \frac{Y_{Pilot}}{X_{Pilot}} \tag{6}$$

Where Y_{Pilot},$X_{Pilot} \in \mathbb{C}^{\frac{N_f}{2} \times N_{Pilot}}$ representing received and transmitted signals respectively at pilot positions.
The matrix $\hat{H}_{LS}$ is concatenated to be one vector column $\in \mathbb{C}^{\frac{N_f N_{Pilot}}{2}}$, then it is spitted into real and imaginary parts to have a size of $\mathbb{R}^{\frac{N_f N_{Pilot}}{2} \times 2}$, this latter is the input of HA02.

Fig.4 shows the HA02 components, involving the transformer encoder (multi-head attention and feed-forward network) and the residual convolutional architecture. A fully connected layer resizes the input $\hat{H}_{LS}$ to $\mathbb{R}^{\frac{3N_f N_{Pilot}}{2} \times 2}$ to have 3 sub-inputs which are the key, the query, and the value $K, Q, V \in \mathbb{R}^{\frac{N_f}{2} \times 2 \times N_{Pilot}}$, then we calculate the dot-product attention by (7).

$$\text{Attention} = \text{softmax}\left(\frac{QK^T}{\sqrt{\frac{N_f}{2}}}\right)V \tag{7}$$

The input of the decoder $\in \mathbb{R}^{\frac{N_f N_{Pilot}}{2} \times 2 \times 1}$ passes through a convolutional layer which has N_{filter} filters with a kernel size of $2 \times 2 \times 1$ followed by a second convolutional layer having N_{filter} filters each one of a kernel size of $2 \times 2 \times N_{filter}$.After, the ReLu layer and one convolutional layer process the result before being treated by the Add & Norm layer. The fully connected layer transforms the result from $\mathbb{R}^{\frac{N_f N_{Pilot}}{2} \times 2 \times N_{filter}}$ to $\mathbb{R}^{N_s N_f \times 2 \times N_{filter}}$ and the last convolutional layer generates an output $\in \mathbb{R}^{N_s N_f \times 2}$

4 Simulation Results

In simulations, the MSE is the measure to analyze the error between the real and estimated channels, expressed as

$$MSE(\hat{H}, H) = \frac{1}{N_s N_f} \sum_{i=1}^{N_s} \sum_{j=1}^{N_f} \|\hat{H}_{ij} - H_{ij}\|_2^2 \tag{8}$$

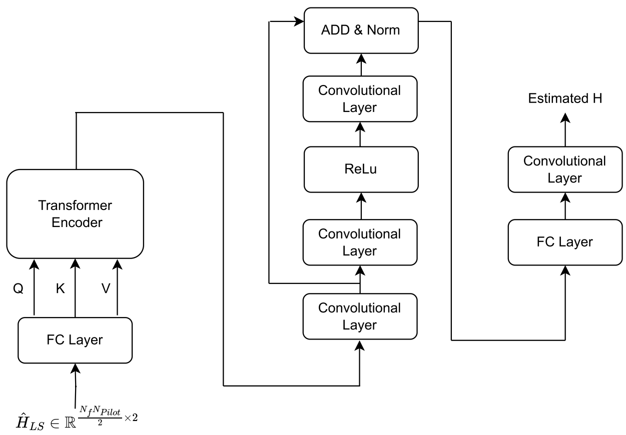

Figure 4. Hybrid transformer architecture (HA02).

Where $\hat{H}_{ij}$ is the estimated channel at subcarrier i and OFDM symbol j and H_{ij} is the corresponding real channel.
The training dataset is generated on parameters described in Table 1

Table 1. Training parameters

Parameter	Value
K	4.5dB
Carrier Frequency	0.3 Thz
a_w	0.6dB/Km (Fog Attenuation)
	3dB/Km (Rain Attenuation)
Bandwidth	3 Ghz
SNR Range	10dB to 30dB
Modulation order	16-QAM
z	150m
Minibatch size	128
Maximum epoch	50

The chosen K value is used according to [14], as most K values are observed to be within the range of -10 to 10dB in Urban, Suburban, and Rural/Open Areas.

4.1 MSE over SNR under Different Weather Attenuation

Fig.5 and Fig.6 present the MSE results of each method when tested on the Rician Thz channel by varying SNR between 0 dB and 40 dB with maximum Doppler shift between 0 Hz and 13.88 kHz. HA02 surpasses the LS and transformer(TR) methods by using the attention mechanism in a turbulent channel with fog and rain attenuation at a precipitation rate of 2 mm/h accompanying the presence of FSPL. For all SNRs at fog attenuation, transformer architecture has maintained the same performance. At a high SNR range from 20 dB, the LS and transformer have around the same MSE. Contrary to Rayleigh fading, ReEsNet outperforms HA02 in Rician fading, Hybrid architecture has also saved the same performance from 10 dB to 40 dB. All tested methods have the same behavior

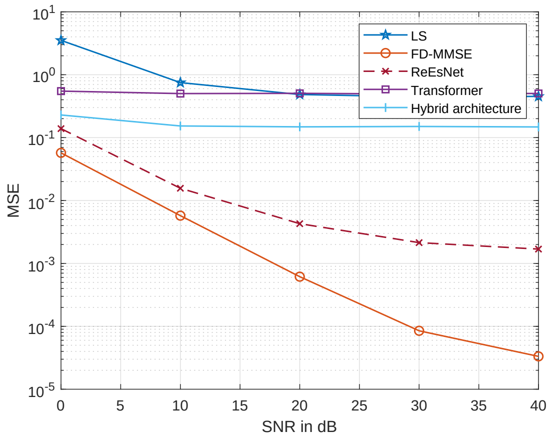

Figure 5. MSE over SNR range under fog attenuation.

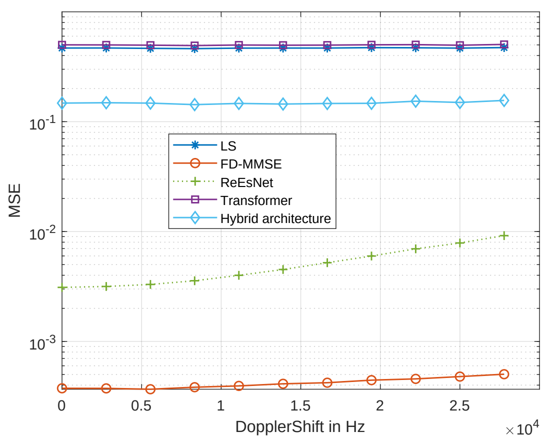

Figure 7. MSE over Doppler Shift range under fog attenuation.

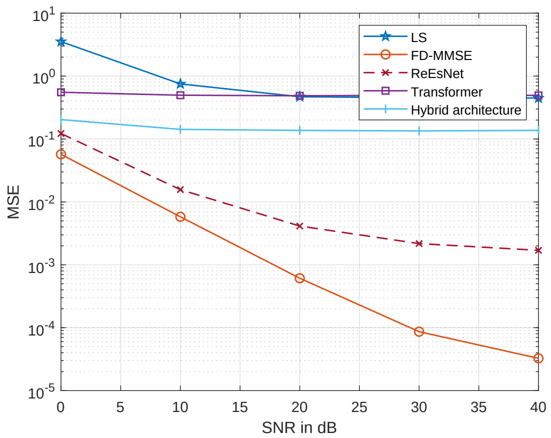

Figure 6. MSE over SNR range under rain attenuation.

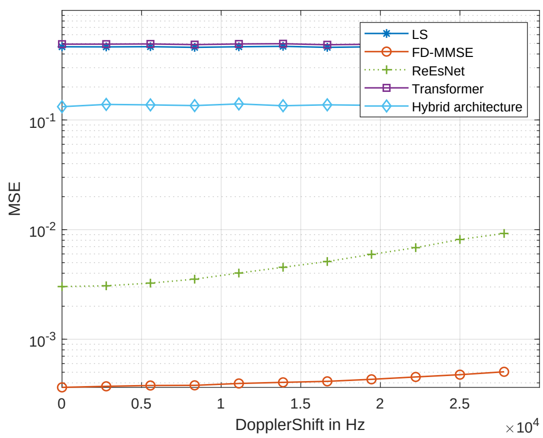

Figure 8. MSE over Doppler Shift range under rain attenuation.

in different weather conditions (rain, fog) under the same FSPL, because the adopted model (Rician) takes into account the existence of the LOS component which.

4.2 MSE over Doppler Shift Range under Different Weather Attenuation

Each maximum Doppler shift from 0 Hz to 27.77 KHz at a particular SNR=10dB is tested on 4000 channel realizations. Fig.7 and Fig.8 present the MSE results of analyzed methods by varying mobile speed from 0 Km/h to 100 Km/h. HA02 has also surpassed TR and LS methods, and they have guarded approximately the same MSE over all Doppler Shifts. As in section IV.A, the simulation shows that bilinear interpolation used in the LS method is inefficient compared to neural network interpolation especially in the Doppler shift context. Furthermore, weather conditions don't affect channel estimation accuracy using the treated methods.

Tables 2 and 3 summarize the simulation results for MSE at SNR=0 dB and Doppler shift equals 27777 Hz.

Table 2. Simulation results for SNR=0 dB

Technique	Fog	Rain
LS	3.51	3.53
FD-MMSE	0.05	0.05
ReEsNet	0.13	0.12
Transformer	0.54	0.55
Hybrid architecture	0.22	0.20

Table 3. Simulation results for Dopplershift=27777 Hz

Technique	Fog	Rain
LS	0.472	0.472
FD-MMSE	0.0005	0.0005
ReEsNet	0.009	0.009
Transformer	0.504	0.496
Hybrid architecture	0.156	0.141

5 Conclusion

This paper conducts a comprehensive survey of Rician channel estimation using the Attention mechanism for Thz communication. The Hybrid Architecture HA02, under study, combining the transformer encoder and the residual neural network as decoder, is compared with other channel estimation solutions. By focusing on important channel features, our simulations show superior estimation compared with the LS method and transformer for channel estimation. HA02 decreases the MSE by 34.95 % for the SNR range from 20 dB to 40 dB.

6 Perspectives

For future studies, there remain many potential applications of the attention mechanism in channel estimation. One scenario is multi-user multiple input multiple output (MU-MIMO), a crucial technique of modern wireless communication systems, particularly in 6G mobile networks. Also, this technique could be studied for reconfigurable intelligent surface (RIS) aided massive multiple-input multiple-output systems.

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