A Deep Model-Based Channel Interference Mitigation for OTFS Signals in ISAC Systems

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In recent years, Orthogonal Time Frequency Space Modulation (OTFS) has gained popularity in integrated sensing and communications (ISAC) system due to its robustness against Doppler offset and delay changes. Traditional pilot-based methods for accurate channel parameter estimation are complex and struggle with rapidly changing channel conditions. In this letter, we propose a deep encode-decode network (DED-Net). It uses DL to automatically learn and eliminate channel interference from OTFS signals. The framework employs a deep encoding and decoding network, similar to a filter, learning complex signal features to effectively remove interference. Our experiments demonstrate DED-Net's ability to eliminate interference in OTFS modulation signals, offering an alternative to pilot-based methods and showcasing DL's potential for ISAC systems.

Introduction: Orthogonal time frequency space modulation (OTFS) modulates information code elements more efficiently than orthogonal frequency division multiplexing (OFDM) by utilizing the approximate smoothness of the time-delay Doppler domain channel and modulating information code elements in the time-delay Doppler domain. Therefore, it has a greater advantage in time-frequency dual-selective channels. Since OTFS modulation is able to combat high delay and Doppler shifts, it is considered as an effective technology for ISAC in high-mobility scenarios [1–6]. With the development of next-generation mobile communication technologies, 6G needs to address high-speed communication in high mobility scenarios, such as high-speed rail, drones, and unmanned vehicles [7-10].

In high-speed mobility scenarios, wireless signals arrive successively at the receiver after reflection by obstacles like buildings and vehicles, creating multipath effects with varying delays and fading. This results in frequency selectivity, and the relative motion of transceivers imparts Doppler frequency bias to each signal path, causing time-domain selectivity, known as a time-varying channel.

In high-speed mobile scenarios, most channels are time-frequency dual-selective channels. In next-generation system, OFDM optimally utilizes spectrum by leveraging subcarrier orthogonality. However, at high speeds, subcarrier orthogonality is compromised, degrading OFDM performance. Traditional OFDM is inadequate for these scenarios. In time-invariant, frequency-selective channels, guide frequency-based channel estimation remains valid for the entire frame. For time-varying channels, continuous updates are needed. To minimize bit errors in high-speed scenarios, inserting numerous frequency guides is essential. However, excessive cyclic prefix (CP) and frequency guide overhead reduce spectrum efficiency and increase costs.

To solve communication challenges in high-speed mobile scenarios, the OTFS modulation scheme was proposed in [11]. OTFS was demonstrated in [12–14] to be more suitable for communication in high-speed mobile scenarios than conventional modulation methods. OTFS performs modulation and demodulation of signals in the delayed Doppler domain [15–17]. The time-frequency dual-selective channel can be represented as a sparse channel with multiple taps in the delayed Doppler domain. Channel estimation in this domain effectively serves as channel estimation for the entire signal block. The frequency domain signal can be converted to the delay domain signal using the inverse fast Fourier transform (IFFT), and signals inserted in the delay Doppler domain are transformed using the inverse Sim Fourier transform (ISFFT).

However, practical OTFS application still faces challenges [17]. ISAC systems struggle to achieve time-frequency dual orthogonality with transceiver filters, often resorting to rectangular filters. High-speed mobile scenarios introduce inter-carrier interference and inter-symbol interference in OTFS signals [18]. In ISAC systems, one symbol block represents multiple consecutive multi-carrier symbols, leading to a large channel matrix when representing the received signal as a product of the transmitted signal and the channel matrix. Traditional linear interference cancellation methods demand significant time and space resources. Nonlinear detection methods rely on fixed parameters from simulations, limiting optimization. OTFS channel estimation using impulsive signals simplifies the process with a threshold, but there's room for improvement in these methods.

With increasing hardware computing power, deep learning (DL) algorithms have become pivotal in various fields, including image processing, natural language processing, and language recognition [19, 20]. DL employs complex multilayer neural networks for enhanced expressive-ness. Optimizing DL has benefited from big data, improved algorithms, and better hardware. DL consists of two phases: training and application. During training, data is input, and actual outputs are compared to desired results. The backpropagation algorithm iteratively adjusts neural network weights. In the application phase, the trained model quickly processes real data, reducing online task execution time but requiring offline training. DL's advancements also contribute to OTFS signal noise reduction in communications.

In this letter, inspired by voice noise reduction [21], we leverage an Encoder-Decoder network to learn a matrix that can encode the OTFS signal to the original signal. The main contributions of this paper are summarized as:

1. A novel network architecture DED-Net is proposed for channel interference elimination for OTFS signals under various SNRs conditions. DED-Net contains an encoder and decoder modules. The DED-Net can effectively eliminate channel interference for OTFS.
2. In the proposed model, richer features are fused by setting cascaded structures, which consist of a down-sampling module and an up-sampling module. This process allows the model to focus more on the key feature dimensions to achieve matrix decomposition.
3. Numerical experiments verify the effectiveness of the proposed method under different SNR conditions. The original coding information of the separated signal is validated by bit error rate.

Motivation: In ISAC systems, achieving the ideal transceiver filter, meeting the time-frequency dual quadrature requirement, is challenging. Rectangular filters are a practical but imperfect alternative, introducing interference in high-speed mobile scenarios. OTFS symbol blocks correspond to multiple multi-carrier symbols, leading to a large channel matrix [22]. Traditional linear interference cancellation methods have high complexity. Nonlinear methods require preset parameters based on simulations, challenging to optimize. Traditional OTFS channel estimation with impulsive signals as guides results in errors when setting a threshold for signal filtering.

In OTFS systems, where the channel is a 2D matrix in the delayed Doppler domain, we propose a deep interference elimination network to effectively reduce interference. This network addresses traditional interference cancellation and channel estimation challenges by using DL to estimate and eliminate interference in ISAC systems.

$$r'(t) = M(r(t)), \tag{1}$$

where $M(\cdot)$ is the deep noise eliminate network. We hope the denoised data is as same as the original sent data as possible, and the constraint optimization can be expressed as

$$Minimize\ D(r'(\mathrm{t}), \mathrm{s}(\mathrm{t})), \tag{2}$$

where $D(\cdot)$ denotes the distance metric function. Through the optimization of the model, the transmitted signal and the model-processed signal are as same as possible to achieve effective noise elimination for ISAC systems.

The proposed Network:

Time Delay Doppler Interference Elimination Network: High-speed communication systems often have transient channel changes, making it challenging to learn channel parameters quickly using traditional pilot modes, which have high complexity. While in an OFDM system, a CP is designed to convert the linear convolution of the physical channel into cyclic convolution, reducing inter-symbol interference but decreasing transmission efficiency. However, the data-driven deep learning model offers a robust and automated method to address the time-delay Doppler problem in high-speed motion. In this study, an end-to-end algorithm with high robustness was developed to automate time delay Doppler elimination.

The proposed time delay Doppler interference elimination algorithm is an Encoder-Decoder structure, as illustrated in Figure 1. The encoder in the upper part consists of dry convolution, average pooling, batch normalization, and an activation function. Typically, the input original OTFS data is down-sampled, and the decoder below is up-sampled to recover the data and provide a prediction for each pixel.

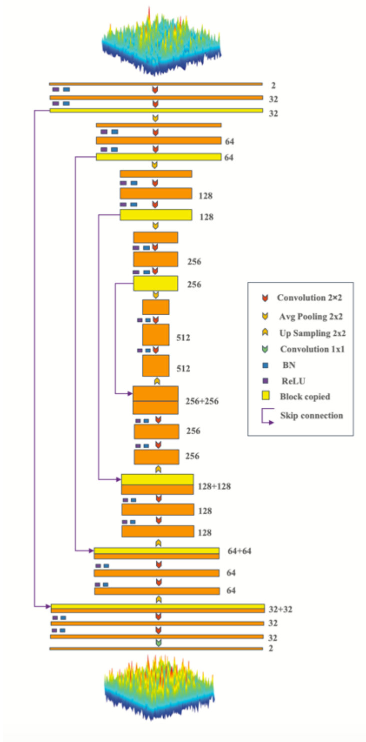

Fig 1 An illustration of the proposed DED-Net system.

The encoder contains four encode blocks, with each submodule having two convolution layers. Each convolution processed data is then subjected to Batch Normalization (BN), which can enhance network convergence, control gradient explosion or disappearance, and prevent overfit-ting. The data are then passed through the ReLU activation function to introduce nonlinearity. At the end of each submodule, a down-sampling layer is implemented through the Average Pool. The input data format is 2 × 64 × 64, and the resolutions of the 1-4 modules are 32 × 64 × 64, 64 × 32 × 32, 128 × 16 × 16, and 256 × 8 × 8, respectively.

The decoder consists of four modules, increasing data dimension through up-sampling until it matches the input signal resolution. Jump cascades connect up-sampling results to sub-modules in the encoder, propagating pre-encoded information. The segmentation map contains pixels with full context from the input image, without fully connected layers. The proposed deep learning-based algorithm effectively eliminates time delay Doppler interference in high-speed motion, offering robustness and an end-to-end architecture for communication systems.

Learning Process: The learning process considers the waveform characteristics of the signal, and the scale-invariant source-to-noise ratio (SI-SNR) is utilized as the loss function to avoid being influenced by the amplitude size. While signal-to-noise ratio (SNR) is defined as the power ratio of signal to noise, SI-SNR is used to mitigate signal variations through regularization. To further improve signal separation and recovery, we combine mean square error (MSE) to optimize the back-propagation process and train the dataset's learning. The loss function for training optimization is defined as:

$$Loss = -SI\text{-}SNR + MSE, \tag{3}$$

where $SI\text{-}SNR$ is defined as:

$$\begin{cases} s_{target} = \frac{\langle \hat{s}, s \rangle}{\|s\|^2}, \\ e_{noise} = \hat{s} - s_{target}, \\ SI - SNR = 10log_{10} \frac{\|s_{target}\|^2}{\|e_{noise}\|^2}, \end{cases} \tag{4}$$

where $\hat{s}$ is the decoded signal, and s denotes the original OTFS signal. $\langle \hat{s}, s \rangle$ signifies $\hat{s} \times s$ and then the summation operation. $\|s\|^2$is the second order norm of s.MSE is presented as:

$$MSE = \frac{1}{n} \sum_i^n (\hat{s} - s). \tag{5}$$

By optimizing $SI\text{-}SNR$ and MSE, the interference is eliminated, and recovering the raw OTFS signal.

Simulations and Analysis:

Data and Settings: To evaluate the performance of the proposed scheme, experimental data is simulated using the Matlab2019b plat-form. Specifically, each frame contains 64 symbols, and there are 64 subcarriers. The signal in the time-delay Doppler domain, modulated by 64QAM, is transformed into the time-frequency domain signal by SFFT, which is then mapped to the time domain by the Heisenberg transform. After channel conversion, the time-domain signal is transformed into the time-frequency domain signal using the Wigner transform.

The complex-format signal is transformed into two-channel data according to the In-phase/Quadrature parts to serve as input for the neural network. The time-frequency domain signal obtained through the SFFT transform serves as label data for model learning. The channel SNR ranges from -5 dB to 20 dB, and the input data dimension is 64 × 64 × 2. A total of 60,000 experimental data points are generated, with 7000 pieces in the training set, 1000 pieces in the validation set, and 2000 pieces in the test set. The experiment was executed using an NVIDIA GeForce GTX 1080Ti GPU.

The performance of proposed scheme: To assess our scheme's performance, we compared it with traditional methods, including SVD, PCA, LSMMSE, and Wavelet (WT). Figure 2 displays the BER comparison between our algorithm and the baseline methods. Our algorithm achieves the following BERs: -5 dB (25%), 0 dB (18%), 5 dB (6.8%), 10 dB (2%), and 15 dB (0.2%). In contrast, traditional algorithms yield BERs ranging from 33% to 51% at -5 dB SNR, gradually decreasing with increasing SNR. At SNR = 20 dB, baseline methods achieve BERs between 1.1% and 1.7%. Our results highlight the superior noise impact reduction and error rate improvement of our algorithm compared to traditional methods, underscoring its robust performance.

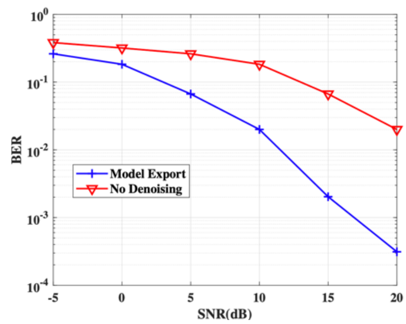

Fig 2 The BER value comparison of the proposed scheme and baseline methods.

Figure 3 compares NMSE results of our algorithm with baseline algorithms across various SNRs. At -5 dB SNR, our algorithm achieves an NMSE of -1.52. The NMSE values at other SNRs are: 0 dB (-2.43), 5 dB (-4.67), 10 dB (-6.72), 15 dB (-7.45), and 20 dB (-9.31). In contrast, the LMMSE algorithm performs less effectively with an NMSE of 0.07 at -5 dB SNR, which is 1.45 worse than our algorithm. At 20 dB SNR, LMMSE outperforms our algorithm with an NMSE of -3.79, which is 5.52 lower. Our algorithm consistently outperforms traditional ones across SNRs.

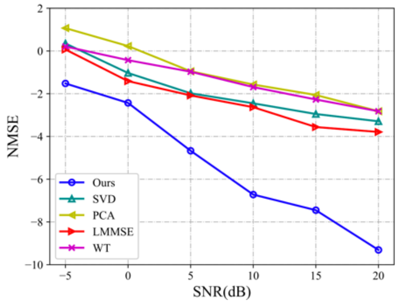

Fig 3 The NMSE value comparison of Doppler delay channel interference elimination methods for OTFS based on the proposed method.

Figure 4 presents KL results comparing our algorithm with baseline methods based on experimental data. At -5 dB SNR, our algorithm achieves a KL value of 0.25. At other SNRs, the KL values are: 0 dB (0.18), 5 dB (0.15), 10 dB (0.11), 15 dB (0.09), and 20 dB (0.06). In contrast, the LMMSE algorithm performs less effectively with a KL value of 0.27 at -5 dB SNR, which is 0.02 higher than our algorithm. At 0 dB SNR, LMMSE's KL value is 0.23, which is 0.05 higher. At other SNRs, baseline methods consistently have higher KL values compared to our algorithm.

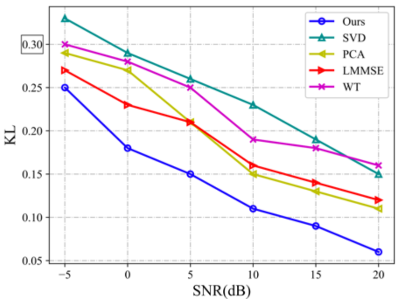

Fig 4 The KL value comparison of Doppler delay channel interference elimination methods for OTFS based on the proposed method.

Based on experiments, the proposed algorithm outperforms traditional methods at various signal-to-noise ratios, indicating its effectiveness in reducing noise and distortion. Comparing it to the baseline algorithm underscores its accuracy in signal estimation. These results offer insights for designing and optimizing signal processing algorithms, with wide-ranging applications. Future research can examine the algorithm's performance in complex scenarios and explore its extensions and applications in diverse domains.

Conclusion: In this letter, we introduce a groundbreaking channel estimation approach for ISAC systems using our novel DL-based model, DED-Net. Unlike traditional methods, DED-Net employs an end-to-end deep encode-decode convolutional architecture. It excels at eliminating channel interference and directly recovering OTFS symbols. Extensive simulations confirm its advantages, emphasizing deep learning's potential in addressing OTFS channel interference. Our findings offer a transformative perspective on channel estimation, revealing limitations in traditional methods. DED-Net's success paves the way for deep learning in ISAC systems, showcasing its adaptability in complex interference scenarios.

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