Enabling Data-Driven OTFS Modulation for 6G Hyper Reliable High-Mobility Communications

Jianzhe Xue, Tiankai Jiang, Haohai Huang, Zitian Zhang, Haibo Zhou, and Xuemin Shen

Abstract

Orthogonal time frequency space (OTFS) modulation has emerged as a promising solution for hyper-reliable high-mobility wireless communications over channels with severe Doppler effect. By mapping symbols into the delay-Doppler (DD) domain, the channel effect of OTFS becomes a two-dimensional circular convolution between symbols and channel responses. However, the physical layer algorithms of OTFS are challenging due to the complexity of two-dimensional signal processing. To this end, this article explores the potential of data-driven approaches for OTFS systems since deep learning (DL) is powerful in extracting both linear and non-linear complex relationships from high-dimensional data. The DD domain signals are easily transferred to grid, graph, or sequential data that are compatible with various DL models. We investigate how these data-driven approaches can be applied to OTFS communication systems, including transmitter and receiver. Furthermore, we propose shift padding (SP) for the convolutional neural network (CNN) to address its inability to handle edge symbols due to the limited reception field. We validate the effectiveness of SP-enhanced CNN for OTFS channel equalization on vehicular channels, and the results show that, for low signal-to-noise ratios, the data-driven approach can achieve higher reliability compared with the conventional algorithms.

Introduction

The demands of ubiquitous and reliable connectivity in the sixth-generation (6G) networks pose unprecedented challenges for hyper-reliable high mobility wireless communications (HMWC) from various mobile devices, including vehicles, trains, unmanned aerial vehicles (UAVs), and satellites [1]. To satisfy the stringent requirements of HMWC, 6G networks have to cope with the issues of high mobility in dynamic environments [2, 3]. Unlike quasi-static channels that only have frequency-selectivity, the channels of HMWC scenarios also exhibit time-selectivity due to the Doppler effect caused by the relative movements among the transmitters, scatterers, and receivers. The current orthogonal frequency division multiplexing (OFDM) modulation using the time-frequency (TF) domain suffers from severe inter-carrier interference (ICI) when applied on the doubly-selective channel, degrading its channel equalization and reliability performance [4]. The channel property of HMWC necessitates the investigation of novel modulation schemes for the physical layer.

Orthogonal time frequency space (OTFS) modulation, as the two-dimensional modulation scheme that maps data symbols into the delay-Doppler (DD) domain, is emerging as a promising solution for HMWC [5]. Each DD domain symbol is expanded in the entire TF domain to explore the channel diversity, enabling a nearly uniform channel effect on each transmitted symbol [6]. OTFS transforms the TF domain channel, which undergoes frequency and time fading, into the DD domain channel, which remains approximately constant. The DD domain channel effect is a two-dimensional convolution between data symbols and channel responses. This transformation helps to overcome the limitations inherent in the TF domain processing of OFDM.

Although OTFS modulation has demonstrated great potential for hyper-reliable communications in high-mobility scenarios, its algorithms and deployment still face some challenges [7]. Physical layer algorithms for OTFS, such as channel equalization in the DD domain, are inherently complex because they need to consider both Doppler shift and delay spreading. Conventional mathematical methods may struggle to deal with two-dimensional DD domain signals efficiently, while repeated iterations will consume massive computational resources [8]. Recently, the application of data-driven approaches with deep learning (DL) has garnered increasing attention in communications. As for OTFS systems, DL can offer a refined understanding of the multifaceted relationships in high-dimensional DD domain data, thus enabling more effective and robust signal processing techniques.

Data-driven approaches hold significant promise for enhancing the performance of OTFS systems [9–12]. DL demonstrates its profound capability in processing high-dimensional complex data types, including grids, graphs, and sequences. Fortunately, the DD domain signals can be conveniently transformed into these data formats, thereby aligning well with different DL models. For instance, OTFS signals can be interpreted as grid data, facilitating the application of convolutional neural networks (CNNs). Additional-

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ly, the spatial correlations inherent in OTFS data across different grids can be abstracted to form graph data. Moreover, the temporal correlations observed in channel fading and signal variations lend themselves to sequential data representations. This adaptability makes DL an excellent tool for handling DD domain signals in OTFS systems. With proper DL models, data-driven approaches can reduce algorithmic complexity while increasing reliability in high-mobility scenarios.

This article introduces the suitability of OTFS modulation for HMWC, investigates the potential of data-driven approaches in OTFS systems, and proposes a novel padding method to enable CNNs to be used for OTFS receivers. The contributions are as follows:

- We introduce the suitability of OTFS modulation for hyper-reliable HMWC. Moreover, the challenge of OTFS deployment and the benefits of using data-driven approaches for OTFS is discussed.
- We investigate some DL approaches that are suitable for DD domain signal processing and explore how these DL approaches can be applied to OTFS systems from both DL and OTFS perspectives.
- We propose a novel padding method called shift padding (SP) for CNN to address its inability to handle some edge symbols whose information is located on the other pair of edges due to the limited reception field.

The remainder of this article is organized as follows. The next section introduces the OTFS modulation for HMWC. Following that, we discuss how data-driven approaches can be applied to OTFS systems. We then propose the SP method for CNNs and evaluate its performance for OTFS channel equalization. Finally, we conclude this article.

Overview of OTFS for High Mobility Wireless Communication

High Mobility Wireless Communication Scenarios

Hyper reliable HMWC focuses on establishing and maintaining robust wireless connections with high-mobility devices, and HMWC scenarios are integral to the successful deployment and functioning of 6G networks.

Satellite Communication: Satellite communication leverages artificial satellites to provide global coverage and universal connectivity. Satellites can act as a backup communication system when terrestrial infrastructure is unavailable, ensuring reliable and resilient communication in 6G, even under challenging situations. Relative to ground users, low earth orbit (LEO) satellites have a stunning speed of about 7 km/s.

UAV Communication: UAV communication can be rapidly deployed in designated areas by using UAVs as relay nodes. They provide benefits of agility, maneuverability, and flexibility, which are desirable for 6G networks. UAV communication also faces challenges because of the high speeds of the UAVs, particularly the fixed-wing UAVs that can fly faster than 500 km/h.

High-Speed Railway Communication: High-speed railway communication aims to provide a high-quality travel experience and ensure reliable operations for the passengers and operators. Railways are considered one of the most important forms of ground transportation. China has developed one of the most advanced and extensive high-speed railway networks in the world, with speeds of up to 350 km/h.

Vehicular Communication: Vehicular communication enables vehicles to communicate with each other and the surrounding environment. It facilitates the information exchange among vehicles, roadside infrastructures, and cloud-based platforms, which supports the development of intelligent transportation systems with the 6G vehicular network. The speeds of vehicles can reach up to 100 km/h.

Linear Time-Variant Channel

In HMWC scenarios, the linear time-invariant (LTI) channel model assumption, which only has frequency-selective fading, no longer holds due to the presence of multiple scatterers with relative mobility. HMWC channels exhibit significant delay spread and Doppler effect, affecting the signal transmission quality. The delay spread is caused by multi-path propagation, where transmitted signals travel through multiple paths with different delays. This results in temporal dispersion, manifesting as frequency-selective fading. The Doppler effect introduces frequency shifts in signals owing to relative movements among transmitters, scatterers, and receivers. This results in spectral dispersion, leading to time-selective fading. Therefore, the TF domain of the HMWC channel is often doubly selective, exhibiting both time and frequency selectivity simultaneously.

The channels in HMWC scenarios are linear time-varying (LTV) systems, adding complexity to signal transmission and reception. Traditional OFDM modulation operating in the TF domain faces significant challenges in HMWC scenarios since it is designed primarily for quasi-static channels that only have frequency-selective fading. The high mobility of devices results in non-stationary fading coefficients and Doppler spreads inside one OFDM symbol, impairing the subcarrier orthogonality and introducing severe ICI. The doubly selective nature of the LTV channel necessitates the exploration of advanced modulation techniques in the new domain to combat the adverse effects of the TF domain signal processing.

The DD domain channel response characterizes the intensity of scatterers in different propagation delays and Doppler frequency shifts, making it a two-dimensional representation. The channel coefficients in the DD domain directly capture the physical propagation environment in HMWC, which corresponds to a group of obstacles with specific delay values depending on their path length and Doppler values depending on their relative velocities with the transmitter and receiver. This representation exhibits appealing features of sparsity, stability, and diversity, which can greatly facilitate the design and implementation of signal processing algorithms.

OTFS System Model

OTFS modulation is an attractive technique in HMWC scenarios, as it offers strong resilience to delay and Doppler effects. By modulating symbols into the DD domain and spreading them to the

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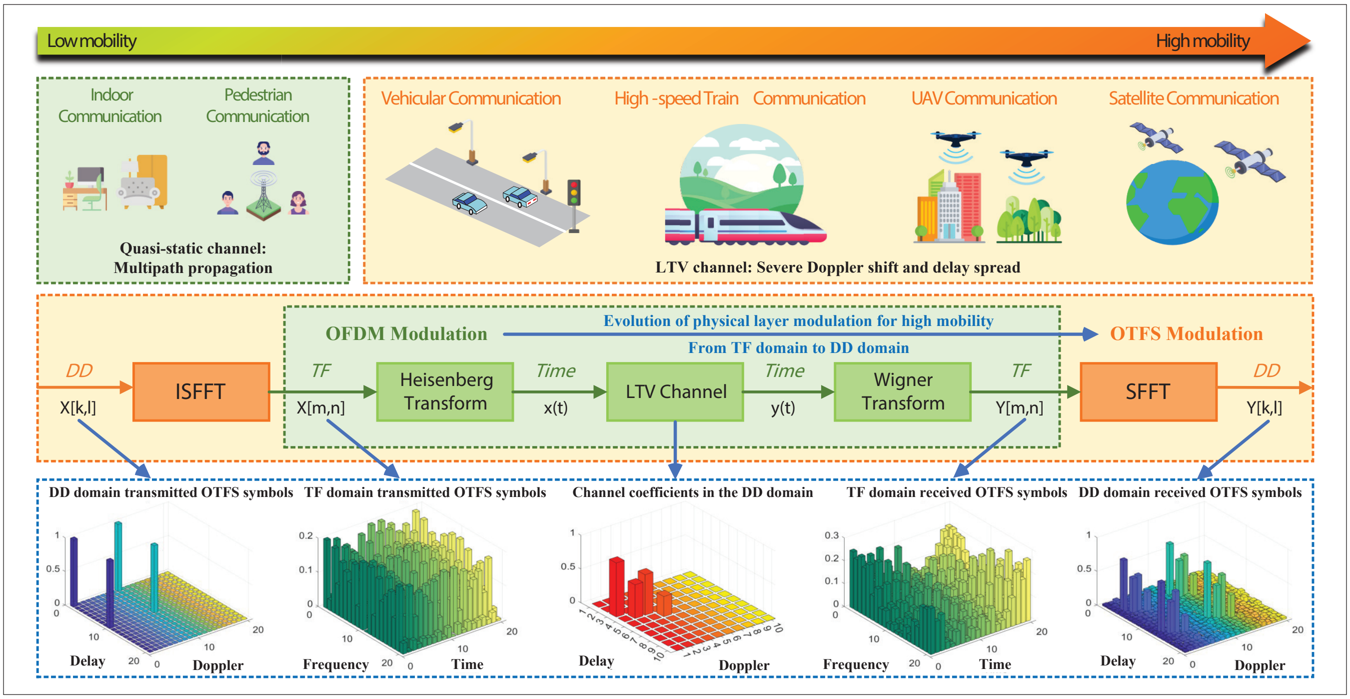

FIGURE 1. OTFS modulation for high-mobility wireless communication.

entire TF domain, OTFS modulation transforms fast time-varying channels to quasi-time-invariant sparse channels in the DD domain. The DD domain channel enables fewer channel parameters and less frequent channel estimations compared to the TF domain, which provides a considerable advantage in the signal processing of HMWC.

Figure 1 shows the OTFS modulation process. Denoting M as the number of delay bins or the number of subcarriers and N as the number of Doppler bins or the number of time slots. The inverse symplectic finite Fourier transform (ISFFT) transforms the DD domain symbols $\mathbf{X}_{DD} \in \mathbb{C}^{M\times N}$ to the TF domain $\mathbf{X}_{TF} \in \mathbb{C}^{M\times N}$. Subsequently, the Heisenberg transform, that is, the inverse fast Fourier transform, is applied to $\mathbf{X}_{TF}$ to obtain the discrete time domain signal $x(t)$ for transmission. The received discrete time domain signal $y(t)$ is firstly transformed to the TF domain $\mathbf{Y}_{TF} \in \mathbb{C}^{M\times N}$ through the Wigner transform, that is, the fast Fourier transform. Finally, the received DD domain symbol matrix $\mathbf{Y}_{DD} \in \mathbb{C}^{M\times N}$ is derived using the symplectic finite Fourier transform (SFFT). Compared with OFDM, OTFS evolves the signal processing from the TF domain to the DD domain through ISFFT and SFFT.

Challenges of OTFS Deployment

There are some challenges in deploying OTFS for hyper-reliable wireless communications in high-mobility scenarios.

Channel Dynamic: Acquiring precise channel state information (CSI) is arduous under high-mobility conditions. The rapid non-linear fluctuations in Doppler shifts and delay spreads render accurate channel estimation exceedingly challenging. Imprecise CSI can lead to elevated error rates and compromise communication reliability.

Signal Complexity: The signal processing tasks of OTFS systems are inherently complex, existing linear and non-linear relationships in data distortion and channel changes. OTFS transposes data symbols into the DD domain, converting signal processing into a two-dimensional challenge that must concurrently address Doppler shifts and delay spreads.

Computational Overhead: OTFS necessitates processing signals within the DD domain, entailing linear manipulation of extensive matrices and the execution of complex transformations that incur substantial computational overhead. These computationally demanding tasks can overburden the processing capabilities of communication systems.

Benefits of Data-Driven OTFS

DL emerges as a powerful tool, facilitating the deployment of adaptive and efficient signal processing algorithms. Data-driven approaches offer substantial benefits for enhancing the performance of HMWC while concurrently reducing the complexity inherent in OTFS systems [10–12].

Computational Efficiency: DL models demonstrate exceptional efficacy in processing large-scale data and identifying complex patterns that are arduous to address analytically. These models can be adeptly trained to perform matrix operations in the DD domain with high efficiency. The feed-forward neural network computation enables greater speed and reduced computational load compared to conventional algorithms, a critical advantage in scenarios with limited processing capabilities.

Learning from Variability: DL models are capable of HMWC channels with significant variability and complexity. Their capacity to extrapolate from historical and present data to forecast future channel states even as they rapidly change significantly refines channel estimation accuracy. Moreover, data-driven approaches adapt to evolving channel conditions through continuous learning from new data, ensuring precise channel estimation under the diverse and fluctuating channels characteristic of HMWC.

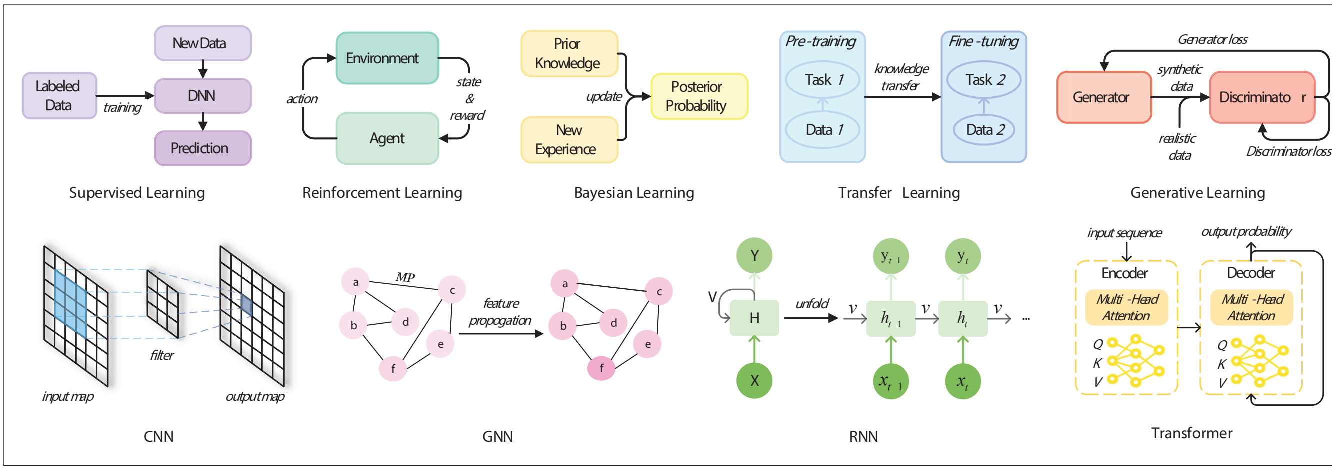

FIGURE 2. Deep learning approaches can be used for OTFS systems.

Robust Feature Extraction: Deep neural networks (DNNs) excel in distilling meaningful features from intricate data sets. The ability of DNN to efficiently extract features from voluminous data allows for better comprehension and depiction of the complex interactions between transmitted and received signals in the DD domain. Even if there is some noise or distortion in the signal, the generalization ability of DNNs can handle it. Such robust feature extraction improves the reliability and accuracy of OTFS.

Handling High-Dimensional Signal: DL inherently manages the intricate and high-dimensional data characteristic of the DD domain. DL models, such as CNNs, excel at identifying and learning robust features from multidimensional datasets. This proficiency is crucial in the DD domain, where comprehending the relationship between delay and Doppler components is vital for precise signal processing. Concurrently, DNN speeds up the processing of multidimensional signals compared to traditional algorithms.

In summary, data-driven approaches can address the challenges of high computational overhead, channel variation, and complex signal processing in OTFS systems by leveraging adaptive processing, robust feature extraction, and algorithmic efficiency. By exploiting the capabilities of DNNs, data-driven approaches emerge as promising tools for enhancing the reliability and efficiency of OTFS systems. However, how to apply data-driven approaches to OTFS systems needs to be explored based on the characteristics of OTFS modulation.

Data-Driven Approaches for OTFS

The implementation of DL techniques in OTFS systems necessitates careful consideration of two primary factors: selecting an appropriate DL training framework tailored to the specific problem characteristics and choosing a suitable DNN architecture that aligns with the nature of the input data. This section discusses the application of different DL approaches in OTFS systems from a DL perspective according to their characteristics and strengths.

Deep Learning Training Frameworks for OTFS

The training framework describes how DL models are trained to learn from data. How to apply different DL training frameworks shown in Fig. 2 to adjust model parameters to perform specific OTFS tasks effectively is discussed as follows.

Supervised Learning: Supervised learning (SL) trains the DNN with data that has associated labels, enabling the DNN to learn the relationships between inputs and their labels. This is suitable for channel equalization and signal detection in OTFS, where DNNs are trained to reconstruct the transmitted data. The received signals with labels are fed to DNN to train direct decoding of the transmitted data without explicit CSI. This implicit learning of channel characteristics is particularly advantageous in dynamic environments, where channel behavior can be relatively complex and stochastic.

Reinforcement Learning: Reinforcement learning (RL) trains agents to learn optimal policies by interacting with environments. The channel states in HMWC scenarios change rapidly over time. RL is able to adapt to such changes and achieve effective sequential signal processing in complex environments, as the agent can dynamically update its policy in response to feedback. For example, the transmitter can be an agent, while the channel and the receiver can be the environment. The bit error rate (BER) is fed back to the transmitter as the reward, which guides the evolution of the transmitter precoding strategy.

Bayesian Learning: Bayesian learning (BL) uses Bayes' theorem to make estimations, updating posterior probability as more evidence is available. Many signal processing modules in the OTFS system, such as channel estimation and equalization, can be effectively reformulated as Bayesian inference problems, where the posterior distribution of the latent variables is computed using expert knowledge.

Transfer Learning: Transfer learning (TL) allows a model to quickly adapt to a relevant task by utilizing previous learning experience rather than training a new model from scratch. This technique enables mobile devices to tackle LTV channels with limited signal samples and constrained computing power, reducing the training cost and enhancing learning efficiency. After pre-training the DNN offline with large-scale data and computing resources, TL can fine-tune the DNN for OTFS systems in a short time by using only a few real-time samples from the dynamic environments.

Generative Learning: Generative learning (GL) produces new data instances that are similar to

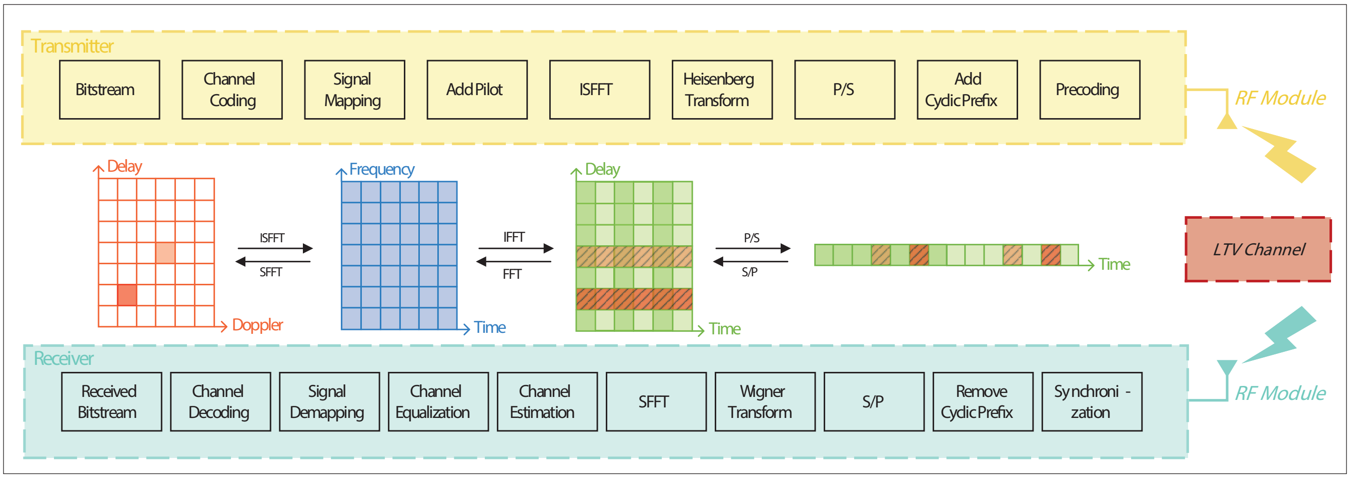

FIGURE 3. Communication process of the OTFS system.

the training data by modeling the underlying distribution of data. In OTFS systems, GL can be trained to enhance signals corrupted by noise or interference, effectively learning the inverse of the channel effects. Specifically, generative adversarial networks (GAN) can use the generator to produce recovered signals and use the discriminator to distinguish the quality of the generated signals. These models can be particularly useful in non-linear or complex channel conditions.

Deep Neural Network Architectures for OTFS

The DNN architectures describe the specific arrangement and configuration of artificial neural networks to improve their ability to learn and generalize from data. The following discusses how to use different DNN architectures, as shown in Fig. 2, to adapt to various OTFS data with different characteristics.

Convolutional Neural Network: CNN is designed to process data with grid structures. The convolutional layer of CNN uses small and localized filters to capture spatial dependencies while disregarding irrelevant information. CNN is well-suited for OTFS systems as the DD domain signals are inherently grid data. Moreover, the parameter sharing scheme in the convolutional layer is similar to the DD domain channel impact, where the channel response for all DD domain symbols is the same. CNN can be trained to perform channel estimation and equalization in OTFS systems, potentially outperforming traditional algorithms in accuracy and efficiency.

Graph Neural Network: Graph neural network (GNN) is designed to process data with graph structures. The fundamental operation of GNN is the iterative message passing within the graph, enabling each node to gather and update information from its neighboring nodes. In the DD domain, signals can be considered as graphs, where the delay and Doppler bins serve as nodes, and the interactions between them are edges. The dynamic message-passing capability of GNNs empowers them to effectively model the intricate spatial and temporal dependencies present in the DD domain, as well as enhance the comprehension of channels with time-varying delays and Doppler shifts.

Recurrent Neural Network: A recurrent neural network (RNN) is designed to handle sequential inputs with unique recurrent architecture, where the output of each step is fed back as input to the next step. The recurrent feedback loop makes RNNs particularly adept at handling temporal data, such as the temporal dependencies in the dynamic LTV channel. By extracting and interpreting these temporal dependencies, RNNs can significantly contribute to key tasks within the OTFS framework, such as channel prediction, estimation, and equalization. For example, RNNs can model and track the variation of CSI, effectively predict future channel conditions, and enhance channel estimation accuracy.

Attention and Transformer: The attention mechanism offers a significant advancement by allowing models to selectively focus on the most relevant parts of inputs. The transformer architecture, which relies on the self-attention mechanism with parallel computing, significantly improves efficiency and addresses the vanishing/exploding gradient problem. The transformer's ability to handle long-range dependencies and focus on relevant parts of the input through its self-attention mechanism makes it well-suited for the dynamic and complex nature of OTFS systems.

Data-Driven OTFS Transceiver

As shown in Fig. 3, the transmitter and receiver of the OTFS communication system contain a number of modules for different tasks. This section describes each module from the perspective of the OTFS system and explores how the DL approach can be integrated into these modules.

OTFS Transmitter Key Technologies

Pilot Design: Pilot design involves embedding pilot symbols within the OTFS data frame, facilitating DD domain channel estimation in OTFS systems. The key to pilot design lies in striking a delicate balance between pilot overhead and estimation accuracy. Utilizing DL for pilot design offers an adaptive pilot allocation, optimizing the structure of pilots based on the timely knowledge of channel conditions. For instance, in vehicular networks, the additional guild symbols for pilots can be dynamically updated with the speed of vehicles [13]. This optimization results in higher spectral efficiency and increased capacity for data transmission while maintaining desired channel estimation accuracy.

Precoding: Precoding refers to the processing of the signal before it is sent over channels, according to CSI's knowledge. The primary goal of precoding is to enhance the strength of the received signals and increase the system's data transmission capacity by spatial multiplexing, beamforming, and mitigating channel impairments. In vehicular networks with fast time-varying channels, by continuously monitoring the historical CSI, the spatial-temporal DNN can provide a predictive precoding approach to reduce the delay while guaranteeing reliability [14].

OTFS Receiver Key Technologies

Channel Estimation: Channel estimation infers the CSI by comparing the received pilots with the original transmitted pilots to find the delay and Doppler spread. DL offers a promising solution by leveraging its ability to capture spatial relationships in the received data frame without relying on specific mathematical models. For example, the deep residual shrinkage neural network based on sparse prior is designed for OTFS channel estimation, showing advantages in terms of estimation performance and computational complexity [11].

Channel Equalization: Equalization is the reversal of channel distortion on transmitted signals. By utilizing the known CSI, equalization compensates for channel distortion and interference, which becomes an integral part of restoring the original transmitted signals. For instance, a neural network-based supervised learning framework is proposed for OTFS equalization, in which a special recurrent neural named reservoir computing is used for one-shot online learning to cope with channel variations among different OTFS frames [15].

Signal Detection: Signal detection refers to the process of identifying and extracting the transmitted information symbols from the received signal in an OTFS system. Traditional algorithms face challenges with slow convergence speeds and high computation complexity. Since the OTFS data is in the two-dimensional DD domain, a two-dimensional CNN based detector is proposed for low time complexity signal detection, in which the data augmentation technique based on the message-passing algorithm is also employed to improve the learning ability of the detector [12].

Case Study: Shift Padding for Equalization

In this section, we introduce the motivation and detailed step of the proposed SP method for the DNN model and evaluate it on the OTFS channel equalization task over the high-mobility vehicular wireless channel.

Shift Padding Method

In the DD domain, the magnitude of delay and Doppler shifts within channel responses is typically minor when contrasted with the dimensions of the OTFS frame. As a result, the two-dimensional circular convolution induced by the channel effect predominantly disperses data symbols to proximate locations surrounding their initial positions. Nonetheless, for symbols situated at the frame's edge, this convolution process can transpose their constitutive information to the diametrically opposite edge. Specifically, it extricates the information from edge symbols at one boundary and reintroduces it from the opposing boundary. Consequently, some information that constitutes these edge symbols is likely to be positioned across the frame, on the opposing edge.

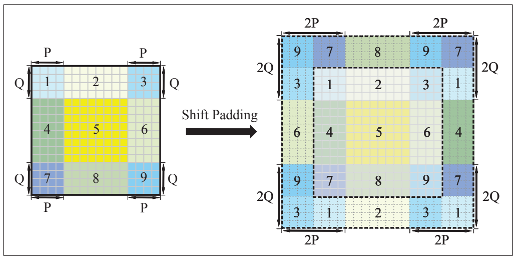

FIGURE 4. The shift padding for CNNs.

The received DD domain data frame is two-dimensional data, which is naturally suitable for CNN to process. However, CNN still faces challenges in processing such data at the OTFS receiver. CNNs employ filters to extract features from data, which inherently limits their receptive field to local information aggregation. This limitation becomes apparent when CNNs are applied at the receiver to process OTFS frames, resulting in an inefficiency in processing edge symbols whose associated information may span across the frame to the opposite edge. To address this issue, we have developed the SP method, which reconciles the limited receptive field of CNNs with the signal characteristics inherent to OTFS. As shown in Fig. 4, the SP method begins by segmenting the received OTFS frame into nine sections. Subsequently, eight sections are duplicated and strategically placed around the perimeter of the original frame, aligning with the principles of two-dimensional circular convolution in OTFS systems. The SP method effectively relocates the information of edge symbols to adjacent positions, thereby enabling their efficient aggregation by the CNNs.

Simulation Parameter Settings

The OTFS frames are configured to a dimension of 64 × 64, utilizing 4-QAM modulation. We set 5.9 GHz as the carrier frequency and 15 kHz as the sub-carrier space. The maximum delay spread is set at 3 unit delay slots. The Extended Vehicular A model (EVA) of 3GPP is used as the channel delay model. The Doppler shift for each path has a uniform distribution corresponding to the velocity of 150 km/h. During training, the received OTFS frames serve as inputs to the CNN model, and the transmitted OTFS frames serve as the training labels. For CNN hyperparameters, the convolution kernel size is 5x5, the total layer is eight layers, and the width of SP is 6. The dataset comprises 1000 frames for this training process.

Results and Discussions

Figure 5a shows the BER performance comparisons between DL-based channel equalization approaches and two traditional methods: linear minimum mean square error (LMMSE) and maximal ratio combining (MRC). The CNN and mobile vision transformers (MobileViT) are evaluated under the premise of unknown CSI at the receiver. The traditional methods encompass both perfect CSI and CSI with a 2 percent estimation error. Zero padding (ZP) is used as a contrast to SP by patching the same number of zeros around the frame. The results indicate that CNNs augmented

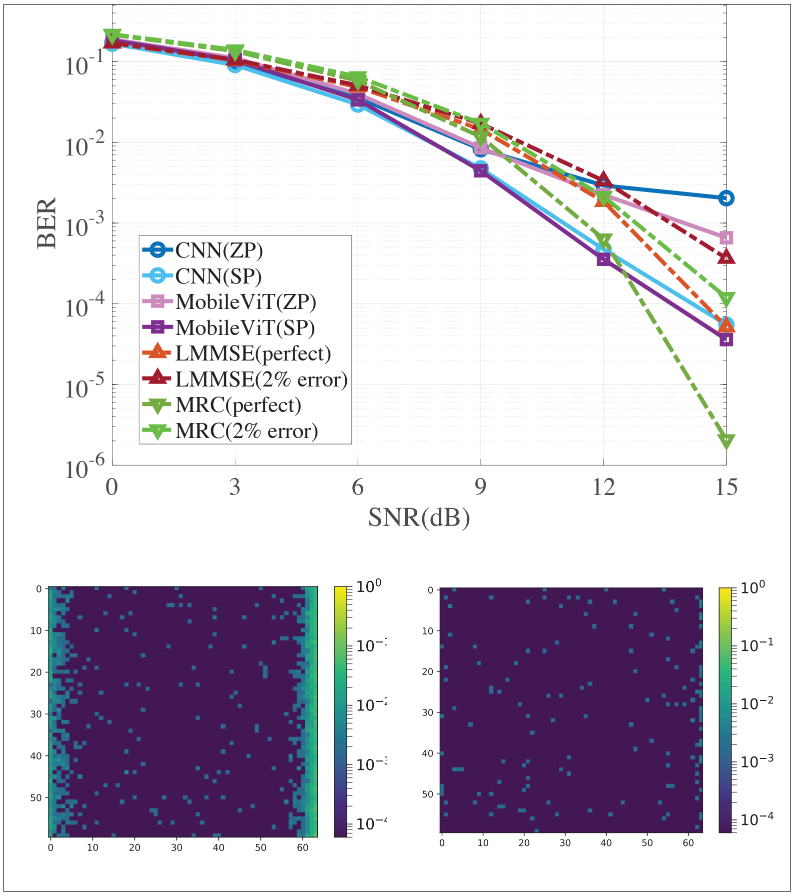

FIGURE 5. The performance evaluation: a) BER performance; b) BER with zero padding; c) BER with shift padding.

with the SP technique exhibit enhanced performance compared to their counterparts without SP, underscoring the significant improvements conferred by the SP strategy. Similarly, SP is also effective for MobileViT, indicating that it is also applicable to models other than CNN. Remarkably, the SP-enhanced CNN outperforms in low SNR environments, surpassing both LMMSE and MRC methods even when they operate with perfect CSI. However, traditional methods only perform well in ideal situations, heavily relying on precise input signals and precise CSI. For complexity, CNN is linear with signal size, while others are all higher than CNN. These results affirm the effectiveness of CNN-based channel equalization and the SP method's role in augmenting equalization precision.

Figures 5b and c show the distribution of average error within frames, demonstrating the efficacy of the proposed SP method for processing edge symbols and enhancing overall performance. From Fig. 5b, the lack of SP results in relatively higher average errors for data bits at the edge, where CNN fails to effectively capture edge information. Conversely, from Fig. 5c, the implementation of SP empowers the CNN to retrieve information at the edges that would otherwise be unattainable, thus diminishing the average BER throughout the DD domain. This comparative analysis of average BER confirms the SP method's significant contribution to enhancing the CNN channel equalization process.

Conclusions

In this article, we have investigated the potential of data-driven OTFS modulation for hyper-reliable HMWC and proposed an SP method designed to bridge the gap between the limited receptive field of CNNs and the signal characteristics of OTFS. We have discussed how the DL approaches can be applied in OTFS systems and validated the effectiveness of SP-enhanced CNN for OTFS channel equalization. The study of data-driven approaches in OTFS should be particularly significant, contributing to enhanced reliability. For future work, we will design the precoding method based on the data-driven approach to improve the reliability of the OTFS system.

Acknowledgments

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