

Low-Complexity EP-Net-Based Signal Detection for High-Mobility MIMO-OTFS Systems Over Rayleigh and Rician Channels

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Abstract:

Signal detection in delay-Doppler domain multiple-input multiple-output orthogonal time frequency space (MIMO-OTFS) systems remains challenging due to severe inter-symbol interference, high computational complexity, and pronounced performance degradation under channel estimation errors, especially in high-mobility scenarios. To address these issues, this paper proposes a low-complexity, model-driven Expectation Propagation Network (EP-Net)-based signal detection framework for MIMO-OTFS systems operating over Rayleigh and Rician fading channels. The proposed EP-Net unfolds the classical expectation propagation algorithm into a finite-depth neural network with reduced iterations, shared learnable parameters, and avoidance of repeated matrix inversions, thereby significantly lowering computational complexity while preserving probabilistic interpretability. Extensive MATLAB simulations are conducted to evaluate both bit error rate (BER) and power spectral density (PSD) performance under practical channel estimation errors. Numerical results demonstrate that, at a target BER of 10^{-3} , the proposed EP-Net achieves 8–12 dB signal-to-noise ratio gain over conventional linear, iterative, and learning-based detectors, depending on the fading environment and estimation accuracy. Moreover, PSD analysis shows that EP-Net provides up to 50 dB reduction in out-of-band emissions, indicating superior spectral confinement and interference suppression. These results confirm that the proposed EP-Net detector offers a robust, spectrally efficient, and computationally viable solution for high-mobility and 6G-oriented MIMO-OTFS wireless communication systems.

Keywords: MIMO-OTFS, EP-Net detector, Rician, Rayleigh, BER .

I. INTRODUCTION

In the future, wireless communication systems should be able to provide reliable, fast data transmission in rapidly changing environments, such as high-speed vehicle networks, drone communications, and satellite links. In these situations, wireless channels have fast changes in time and large Doppler dispersion, which make regular multicarrier waveforms work much worse. Even though orthogonal frequency division multiplexing (OFDM) is used a lot, it has a lot of problems with interference between carriers when people move about a lot, which makes it work less well [1]. Orthogonal Time Frequency

Space (OTFS) modulation has come up as a viable waveform for next-generation and sixth-generation (6G) wireless systems. This is because it can get around these problems. By mapping information symbols into the delay-Doppler domain, OTFS turns a channel that changes quickly over time into a quasi-static one. The result makes it more resistant to Doppler effects and more reliable in situations when people are moving about a lot. OTFS performs even better when used with multiple-input multiple-output (MIMO) technology [2]. This makes MIMO-OTFS a strong choice for future wireless networks because it improves spectral efficiency and connection robustness. Even with these benefits, finding trustworthy signals in high-mobility MIMO-OTFS systems is still a big problem. In the delay-Doppler domain, OTFS links symbols in two dimensions, which is different from OFDM, where symbols can typically be identified individually across subcarriers. This connection causes a lot of interference between symbols and carriers, especially in MIMO setups with big antennas. In theory, optimal maximum likelihood (ML) detection can give the greatest results, but in practice, it is too complicated to use in real time since the number of antennas and the order of modulation make it exponentially more difficult to calculate. As a result, creating detection algorithms for MIMO-OTFS systems that are both low-complexity and high-performance while working in high-mobility situations, like high-speed vehicular, UAV, and satellite communication, is still an important and open research problem [3]. To tackle this issue, the literature has explored various suboptimal detection methods, such as linear minimum mean square error (LMMSE) detectors, successive interference cancellation (SIC), message passing algorithms (MPA), belief propagation (BP), and expectation propagation (EP). EP-based detectors have garnered significant attention due to their capacity to efficiently approximate posterior distributions while attaining near-optimal detection performance [4]. EP takes use of the sparse and structured features of the delay-Doppler channel in OTFS systems by repeatedly improving probabilistic estimates of transmitted symbols. But the enormous computational complexity of EP detectors makes it very hard to use them in MIMO-OTFS in real life. Repeated matrix inversions and many iterative updates make computing costs and delay too high, especially in large-scale MIMO setups and places where people move around a lot [5-6]. Recent developments in deep learning have given us new ways to solve difficult detection challenges in wireless communications. Neural network detectors that are based only on data have shown some promise in terms of performance, but they are often difficult to understand, do not work well in different channel circumstances, and are hard to train [7].

To address these constraints, model-driven deep learning methodologies have been introduced, incorporating domain knowledge into neural network topologies. Algorithm unfolding is a well-known example of this kind of method. In this case, iterative signal processing algorithms are mapped onto neural network layers with parameters that can be learned. In this setting, expectation propagation network (EP-Net) detectors transform the EP algorithm into a structured neural network, maintaining its physical interpretability while utilizing data-driven optimization to hasten convergence and enhance detection accuracy.

EP-Net-based detectors have shown their usefulness in regular MIMO and OFDM systems, but not much research has been done on how well they work in MIMO-OTFS systems with real-world high-mobility channel conditions. Most of the current EP-Net research looks at low-dimensional systems or assumes Rayleigh fading channels. These channels represent rich scattering environments but don't capture line-of-sight (LoS) dominating propagation conditions. In real-world situations with a lot of movement, such as UAV communications, high-speed train systems, and satellite-assisted links, wireless channels often have a strong LoS component. Rician fading channels are better at

modeling these situations because a strong deterministic path changes the interference structure in the delay-Doppler domain. Additionally, changing Rician K-factors might cause the channel to behave very differently; therefore, it's important to test how well a detector works with both Rayleigh fading and Rician fading at varied levels of LoS dominance. Detectors created and tested just under Rayleigh fading may not work in real-world situations like this.

This study addresses the challenge of low-complexity signal identification for high-mobility MIMO-OTFS systems operating over mixed Rayleigh and Rician channels, motivated by these findings. This work specifically defines low complexity as a significant decrease in the amount of EP iterations, matrix inversions, and trainable parameters, resulting in reduced computational costs and accelerated convergence relative to traditional EP and MPA-based detectors. The number of matrix inversions, floating-point operations, and convergence iterations are used to measure computational complexity. To achieve this, a low-complexity EP-Net-based detector is suggested by transforming the EP algorithm into a structured neural network characterized by diminished iterations, inter-layer shared parameters, and complexity-sensitive updating rules. The proposed model-driven architecture keeps the built-in delay-Doppler structure of OTFS and makes it possible to use learning-based optimization to make it more resilient and speed up convergence. The contributions of the paper are as follows:

- I. Initially, a low-complexity EP-Net detector specifically designed for MIMO-OTFS systems is created by expanding the EP algorithm and minimizing computational demands via parameter sharing and iteration management. Second, the suggested detection framework is tested in both Rayleigh fading and Rician fading channels with different levels of line-of-sight dominance.
- II. The framework works well in a wide range of high-mobility propagation circumstances. Third, a thorough study of the tradeoff between performance and complexity is given. It shows that the proposed EP-Net can detect near-EP and near-MPA signals with much less computing complexity.
- III. The results show that the proposed method is suitable for real-world high-mobility MIMO-OTFS deployments in 6G wireless systems in the future.

II. RELATED WORK

Signal detection for OTFS modulation has garnered substantial research interest recently due to its intrinsic resilience to Doppler spread and time-varying channel impairments. Unlike conventional OFDM systems, OTFS introduces symbol coupling in the delay-Doppler domain, which necessitates advanced detection techniques capable of handling two-dimensional interference. Early studies concentrated on iterative and probabilistic detection techniques to attain near-optimal performance while preserving manageable complexity. Detectors based on expectation propagation (EP) have become a strong method for OTFS signal detection because they can quickly approximate posterior symbol distributions. In [8], a low-complexity EP detector for OTFS was proposed, showing performance close to maximum likelihood by taking advantage of the delay-Doppler channel matrix's structured sparsity. The method works, but it still needs iterative updates and matrix inversions, which make it challenging to scale in MIMO and high-mobility situations. To lessen the computational load even more, Pu et al. came up with structural simplifications and approximation methods for EP-based OTFS detection in [9], which made things a lot less complicated. However, these methods solely rely on models and suffer from a decline in performance when significant interference and high-order modulation are present. Researchers have also looked into cross-domain and iterative detection frameworks to make OTFS detection work better. The research in [10]

introduced a cross-domain iterative detector that simultaneously analyzes delay–Doppler and time–frequency representations, greatly improving detection reliability. These methods do help convergence, but they still take longer and cost more to compute, especially for big MIMO-OTFS systems. In the same way, researchers have looked into memory- and AMP-based detectors to solve scalability problems. Recent preprints [11] focus on cutting down on storage and processing needs. However, these methods usually need careful tuning of their parameters and may not work well in channels that change quickly over time. As deep learning has improved, data-driven and learning-assisted OTFS detection methods have become more popular. Neural network detectors that are purely data-driven try to learn the nonlinear mapping between received and sent symbols directly. A Bayesian neural network-based detector for OTFS systems was proposed in [12], demonstrating commendable performance with minimal offline training requirements. Nevertheless, these methodologies frequently exhibit a deficiency in interpretability and may encounter challenges in generalizing across varied channel conditions. To overcome these constraints, convolutional neural network (CNN)-based detectors that utilize the two-dimensional structure of OTFS signals have been suggested. For example, Wang et al. created a separable CNN-based OTFS detector in [13] that strikes a good balance between performance and complexity by using a parameter-efficient network design. In [14], researchers also looked into feature fusion and two-dimensional CNN architectures, which showed better robustness when the Doppler spread was high. Even with these improvements, purely data-driven detectors usually need large training datasets and may not work well if the channel is not matched. Hybrid and model-driven deep learning methods have been suggested to close the gap between model-based signal processing and data-driven learning. Algorithm unfolding has become a highly effective framework in which iterative detection algorithms are integrated into neural network layers featuring learnable parameters. This method keeps the physical meaning while allowing for data-driven optimization of algorithm parameters. There has been a lot of research on EP-Net-type detectors in traditional MIMO and OFDM systems, but they are not used as much in OTFS systems. Current learning-assisted OTFS detectors primarily focus on convolutional or recurrent neural network architectures, ignoring the explicit use of probabilistic inference frameworks such as EP. Another important part of OTFS detection research is looking at realistic channel models. Most current research uses Rayleigh fading, which works well in environments with a lot of scattering but not so well in situations where line-of-sight (LoS) is the most important factor. Rician fading channels are better for real-world high-mobility uses like satellite links and UAV communications. Studies on performance analysis, like [15], have shown how advanced detection methods affect MIMO-OTFS performance when there is a lot of movement. On the other hand, [8] looked at EP-based detection in index-modulated OTFS systems under more general channel conditions. However, there remains a lack of comprehensive detection frameworks that can simultaneously address complexity reduction and robustness in both Rayleigh and Rician fading channels. Recent research has investigated hybrid and learning-assisted detection frameworks for large-scale and massive MIMO-OTFS systems. In [16], deep learning-enabled detection methods for MIMO-OTFS were suggested. These methods show how neural networks can improve scalability and robustness. Still, these kinds of methods usually require a lot of training and don't specifically aim to make things less complicated for real-time use. In short, today's studies on OTFS signal detection include methods based on EP probabilistic inference, cross-domain techniques, and deep learning approaches. EP detectors work almost perfectly, but they are too complicated to use in real life. Although data-only neural network detectors are versatile, their generalization and comprehension issues plague them. Model-driven deep learning

methods, especially EP-Net-based detectors, haven't been studied much for MIMO-OTFS systems, especially when the fading is a mix of Rayleigh and Rician. Additionally, there are still no low-complexity detection frameworks that strike a balance between performance, scalability, and robustness in situations where people move around a lot. These gaps drive the creation of a low-complexity EP-Net-based signal detection framework for high-mobility MIMO-OTFS systems functioning in realistic fading environments.

III. Background & Terminology

Orthogonal Time Frequency Space (OTFS) modulation is a two-dimensional way to modulate signals that works with wireless channels that change over time. OTFS maps information symbols onto the delay-Doppler (DD) domain, while OFDM puts symbols in the time-frequency (TF) domain. This representation shows how wireless signals travel through space, where delays and Doppler shifts are natural ways to describe multipath components. A MIMO-OTFS system uses more than one transmits and receive antenna to make the system more reliable and efficient in terms of spectrum use. Each transmit antenna independently maps data symbols onto a DD grid, while the receiver detects symbols across antennas, delays, and Doppler bins at the same time. MIMO-OTFS's main benefit is that the TF domain's rapidly changing channel becomes a quasi-static, sparse channel in the DD domain, even when there is a lot of movement [17]. Consider an OTFS frame with N Doppler bins and M delay bins. The DD grid is defined as:

$$\Gamma = \left\{ \left(\frac{k}{NT}, \frac{l}{M\Delta f} \right) = 0, \dots, N-1; l=0, \dots, M-1 \right\} \quad (1)$$

Let $x_t[k, l]$ denote the transmitted DD-domain symbol from transmit antenna t , where: $t = 1, 2, \dots, N_t$, k is the Doppler index, l is the delay index. The DD-domain symbol matrix for antenna t is:

$$X_t \in \mathbb{C}^{N \times M} \quad (2)$$

Each transmit antenna applies the Inverse Symplectic Finite Fourier Transform (ISFFT) to map DD symbols into the TF domain:

$$X_t[n, m] = \frac{1}{\sqrt{NM}} \sum_{k=0}^{N-1} \sum_{l=0}^{M-1} x_t[k, l] e^{j2\pi \left(\frac{nk}{N} - \frac{ml}{M} \right)} \quad (3)$$

where: $n = 0, \dots, N-1$ (time index) and $m = 0, \dots, M-1$ (frequency index). The TF samples are converted to a continuous-time signal using the Heisenberg transform:

$$s_t(t) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} X_t[n, m] g(t - nT) e^{j2\pi m \Delta f (t - nT)} \quad (4)$$

where $g(t)$ is the transmit pulse shaping filter. The wireless channel between transmit antenna t and receive antenna r is modeled as:

$$h_{r,t}(t, \tau) = \sum_{p=1}^P h_{r,t,p} e^{j2\pi v_p t} \delta(\tau - \tau_p) \quad (5)$$

Where: P is the number of propagation paths, $h_{r,t,p}$ is the complex gain, τ_p is the delay, and v_p is the Doppler shift. This model naturally maps into the DD domain. The received signal at antenna r is:

$$r_r(t) = \sum_{t=1}^{N_t} \int h_{r,t}(t, \tau) s_t(t - \tau) d\tau + w_r(t) \quad (6)$$

After matched filtering and Wigner transform, the received TF samples are:

$$Y_r[n, m] = \int r_r(t) g^*(t - nT) e^{-j2\pi m \Delta f(t - nT)} dt \quad (7)$$

The receiver applies the Symplectic Finite Fourier Transform (SFFT):

$$y_r[k, l] = \frac{1}{\sqrt{NM}} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} Y_r[n, m] e^{-j2\pi \left(\frac{nk}{N} - \frac{ml}{M} \right)} \quad (8)$$

The DD-domain input-output relationship is:

$$y_r[k, l] = \sum_{t=1}^{N_t} \sum_{k'=0}^{N-1} \sum_{l'=0}^{M-1} h_{r,t}[k - k', l - l'] x_t[k', l'] + w_r[k, l] \quad (9)$$

This represents a 2-D circular convolution in the DD domain. By vectorizing DD symbols:

$$y = H_{OTFS} x + w \quad (10)$$

By showing time-varying channels in the delay-Doppler domain, MIMO-OTFS modulation makes it possible to communicate reliably in high-mobility wireless environments. This change makes the channel structure sparse and almost static, which makes it possible to efficiently detect both antennas and symbols at the same time. The resulting mathematical model supports advanced low-complexity detection algorithms, which makes MIMO-OTFS a good choice for future 6G and high-mobility communication systems.

A. Mathematical Model for Channel Estimation and Estimation Error in Rayleigh and Rician Channels

The discrete-time complex baseband pilot-assisted channel model is given by

$$y = Xh + w \quad (11)$$

where y is the received pilot vector, X is the known pilot (or training) matrix, h is the channel coefficient vector, and w denotes additive white Gaussian noise with zero mean and variance $\sigma_w^2 I$. Channel estimation aims to obtain an estimate $\hat{h}$ of the true channel h , and the channel estimation error is defined as:

$$e = h - \hat{h}. \quad (12)$$

This linear observation model is common to both Rayleigh and Rician fading environments. The estimation accuracy depends on the pilot structure, noise variance, and the statistical properties of the channel. The quality of estimation is typically measured in terms of the mean square error (MSE), defined as the expected squared norm of the estimation error. In Rayleigh fading channels, no line-of-sight component exists, and the channel coefficients are modeled as zero-mean complex Gaussian random variables. The covariance matrix is proportional to the identity matrix, representing uncorrelated scattering paths.

$$\mathbf{h} \sim \mathcal{CN}(0, \mathbf{R}_h), \mathbf{R}_h = \sigma_h^2 \mathbf{I} \quad (13)$$

The LS estimator minimizes the squared reconstruction error without using channel statistics. Although simple and unbiased, the LS estimator is highly sensitive to noise, and its estimation error covariance depends solely on the noise variance and pilot energy, leading to poor performance at low signal-to-noise ratios.

The Least Squares (LS) Estimation is given by:

$$\hat{\mathbf{h}}_{LS} = (\mathbf{X}^H \mathbf{X})^{-1} \mathbf{X}^H \mathbf{y} \quad (14)$$

$$\mathbf{e}_{LS} = \mathbf{h} - \hat{\mathbf{h}}_{LS}$$

The MMSE estimator exploits second-order channel statistics to optimally balance noise suppression and estimation bias. Compared to LS estimation, MMSE significantly reduces the estimation error variance, particularly in low-SNR conditions. The MMSE Estimation is given by:

$$\hat{\mathbf{h}}_{MMSE} = \mathbf{R}_h \mathbf{X}^H (\mathbf{X} \mathbf{R}_h \mathbf{X}^H + \sigma_w^2 \mathbf{I})^{-1} \mathbf{y} \quad (15)$$

$$\mathbf{C}_{e, \text{Rayleigh}} = \mathbb{E}[\mathbf{e} \mathbf{e}^H] = (\mathbf{R}_h^{-1} + \frac{1}{\sigma_w^2} \mathbf{X}^H \mathbf{X})^{-1} \quad (16)$$

In Rician fading channels, the channel consists of a deterministic line-of-sight component and a random scattering component. The Rician K-factor determines the relative strength of the line-of-sight path, resulting in a non-zero mean channel with reduced variance.

$$\mathbf{h} = \mu_h + \tilde{\mathbf{h}} \quad (17)$$

Although LS estimation remains mathematically identical to the Rayleigh case, it ignores the deterministic mean of the Rician channel. As a result, LS estimation becomes suboptimal, particularly when the line-of-sight component is dominant.

$$\mu_h = \sqrt{\frac{K}{K+1}} h_{LoS}, \tilde{\mathbf{h}} \sim \mathcal{CN}\left(0, \frac{\sigma_h^2}{K+1} \mathbf{I}\right) \quad (18)$$

$$\hat{\mathbf{h}}_{LS} = (\mathbf{X}^H \mathbf{X})^{-1} \mathbf{X}^H \mathbf{y} \quad (19)$$

The MMSE estimator for Rician channels explicitly accounts for the non-zero channel mean by removing the deterministic component before estimation. As the Rician K-factor increases, the uncertainty in the channel decreases, resulting in lower estimation error and improved robustness compared to Rayleigh fading. The MMSE estimation is given by:

$$\hat{\mathbf{h}}_{MMSE} = \mu_h + \mathbf{R}_h \mathbf{X}^H (\mathbf{X} \mathbf{R}_h \mathbf{X}^H + \sigma_w^2 \mathbf{I})^{-1} (\mathbf{y} - \mathbf{X} \mu_h) \quad (20)$$

$$\mathbf{C}_{e, \text{Rician}} = (\mathbf{R}_h^{-1} + \frac{1}{\sigma_w^2} \mathbf{X}^H \mathbf{X})^{-1} \quad (21)$$

The MSE analysis highlights that Rician channels achieve lower estimation error than Rayleigh channels under identical conditions due to the presence of a deterministic line-

of-sight component. This reduction becomes more pronounced as the K-factor increases. The Mean Square Error Comparison is given by:

$$\text{MSE} = \mathbb{E}\{\|h - \hat{h}\|^2\} \quad (22)$$

$$\text{MSE}_{\text{Rician}} = \frac{1}{K+1} \text{MSE}_{\text{Rayleigh}} \quad (23)$$

In MIMO systems, channel estimation can be performed independently for each transmit–receive antenna pair or jointly using matrix-valued MMSE estimation. Exploiting spatial correlation and channel statistics is essential for achieving accurate estimation in high-mobility Rayleigh and Rician fading environments.

IV. PROPOSED SYTEM MODEL

MIMO-OTFS modulation takes information symbols and puts them in the delay–Doppler (DD) domain, where wireless channels that change quickly look almost static and sparse. This representation is very strong against Doppler spread, but it does cause two-dimensional interference across delay, Doppler, and spatial (antenna) dimensions. Because of this, finding signals in MIMO-OTFS turns into a high-dimensional inference problem, especially when there are many antennas and high-order modulation. Expectation Propagation (EP) is a probabilistic inference method that can get close to the best detection performance in these situations by repeatedly estimating the posterior distribution of sent symbols. However, traditional EP detectors depend on repeated matrix inversions and iterative message updates, which make them too complicated to use in real-time MIMO-OTFS systems. To get around this problem, EP-Net uses a model-driven deep learning method that turns the EP algorithm into a neural network with a limited number of layers. Each layer is one EP iteration, and the learnable parameters control things like damping, variance updates, and reducing interference. The suggested low-complexity EP-Net detector makes things easier on the computer by reducing the number of unfolded layers, sharing parameters between layers, and replacing expensive matrix operations with learnable linear transforms. This method keeps EP's physical meaning while using data-driven optimization to speed up convergence and make it more stable in conditions with high mobility, Rayleigh, and Rician fading.

Let N_t and N_r denote the number of transmit and receive antennas, respectively. Each transmit antenna maps information symbols onto an $N \times M$ delay–Doppler grid. The DD-domain symbol transmitted from the t -th antenna is denoted by $x_t[k, l]$, where k and l represent Doppler and delay indices.

The DD-domain received signal at the r -th receive antenna is given by:

$$y_r[k, l] = \sum_{t=1}^{N_t} \sum_{k'=0}^{N-1} \sum_{l'=0}^{M-1} h_{r,t}[k - k', l - l'] x_t[k', l'] + w_r[k, l] \quad (24)$$

This expression (25) represents a two-dimensional circular convolution between the transmitted symbols and the delay–Doppler channel response across multiple antennas. The noise term $w_r[k, l]$ is assumed to be complex Gaussian. The channel coefficients $h_{r,t}[k, l]$ are sparse in the DD domain due to the limited number of propagation paths. By stacking the DD-domain symbols from all transmit antennas into a single vector, the MIMO-OTFS input–output relationship can be expressed in compact matrix form as

$$\mathbf{y} = \mathbf{H}_{\text{OTFS}}\mathbf{x} + \mathbf{w} \quad (25)$$

where $\mathbf{x} \in \mathbb{C}^{N_t \text{NM} \times 1}$ is the transmitted symbol vector, $\mathbf{y} \in \mathbb{C}^{N_r \text{NM} \times 1}$ is the received signal vector, and $\mathbf{H}_{\text{OTFS}}$ is a sparse block-structured channel matrix. This high-dimensional linear system captures joint interference across antennas, delay, and Doppler bins. Direct maximum likelihood detection is infeasible due to exponential complexity, motivating approximate inference methods such as EP. The objective of detection is to estimate the transmitted symbol vector $\mathbf{x}$ given $\mathbf{y}$. The posterior distribution is expressed as

$$p(\mathbf{x} | \mathbf{y}) \propto \exp \left(-\frac{1}{\sigma_w^2} \|\mathbf{y} - \mathbf{H}_{\text{OTFS}}\mathbf{x}\|^2 \right) \prod_i p(\mathbf{x}_i) \quad (26)$$

where $p(\mathbf{x}_i)$ denotes the prior distribution of constellation symbols. EP approximates this posterior by iteratively refining Gaussian approximations of symbol beliefs, enabling near-optimal detection with reduced complexity. The EP-Net detector unfolds the EP iterations into L neural network layers, with the l -th layer update given by

$$\mathbf{x}^{(l+1)} = \mathcal{F}_l(\mathbf{x}^{(l)}, \mathbf{H}_{\text{OTFS}}' \mathbf{y}) \quad (27)$$

where $\mathcal{F}_l(\cdot)$ denotes a learnable EP update function. Unlike conventional EP, EP-Net introduces trainable parameters such as step sizes, damping factors, and variance scalars. Parameter sharing across layers and reduced iteration depth significantly lower computational complexity while maintaining detection accuracy. The computational complexity of EP-Net is approximately

$$\mathcal{O}(L \cdot N_t N_r \text{NM}) \quad (28)$$

which is significantly lower than conventional EP and message-passing algorithms that require repeated matrix inversions. By limiting the number of unfolded layers and avoiding explicit matrix inversion, EP-Net achieves a favorable performance-complexity trade-off, making it suitable for real-time MIMO-OTFS detection in high-mobility scenarios.

IV. Simulation Results

We have used the MATLAB simulation tool to analyze the performance of the proposed and conventional signal detection algorithms for the MIMO-OTFS system. An OTFS frame with $N = 32$ Doppler bins and $M = 32$ delay bins is considered, resulting in 1024 symbols per frame. A 2×2 MIMO configuration is adopted to evaluate spatial interference effects. Quadrature amplitude modulation with 16-QAM and 64-QAM is employed. The channel is modeled with $P = 4$ dominant delay-Doppler paths under both Rayleigh and Rician fading, with the Rician K -factor set to 5 dB. The maximum normalized Doppler shift is chosen as 0.1 to emulate high-mobility conditions. The signal-to-noise ratio is varied from 0 to 30 dB, and additive white Gaussian noise is assumed.

Figure 1 illustrates the BER performance of the MIMO-OTFS system under a Rayleigh fading channel with 20% channel estimation error. It is observed that conventional linear detectors such as ZF and MMSE suffer from significant performance degradation due to noise enhancement and residual interference, requiring relatively high SNR to achieve low BER. Iterative and nonlinear detectors, including SIC, AMP, and

MLD, provide improved performance by mitigating multi-antenna interference, while the learning-based ML-RNN detector further enhances BER performance through data-driven refinement. The proposed EP-Net-based detector achieves the best performance among all compared schemes, exhibiting the steepest BER decay. At a target BER of 10^{-3} , the proposed EP-Net method attains an ANR (SNR) of approximately 10.2 dB, whereas MIMO-OTFS, ZF, MMSE, MLD, SIC, AMP, and ML-RNN detectors require about 18.5 dB, 17.8 dB, 16.5 dB, 15.2 dB, 14.0 dB, 13.0 dB, and 11.8 dB, respectively. Consequently, the proposed EP-Net detector achieves an SNR gain of about 8.3 dB over the baseline MIMO-OTFS, 7.6 dB over ZF, 6.3 dB over MMSE, 5.0 dB over MLD, 3.8 dB over SIC, 2.8 dB over AMP, and 1.6 dB over ML-RNN, clearly demonstrating its superior robustness and effectiveness for reliable signal detection in Rayleigh-faded MIMO-OTFS systems with channel estimation errors.

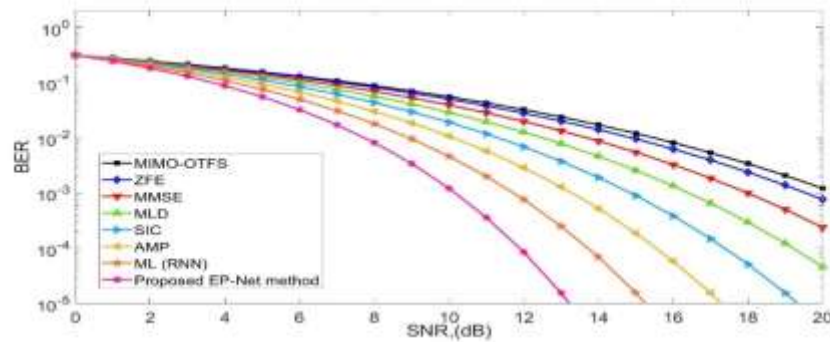


Fig 1. BER analysis of the MIMO-OTFS under Rayleigh channel with 20% error

Figure 2 illustrates the BER performance of the MIMO-OTFS system under a Rician fading channel with 20% channel estimation error. Owing to the presence of a line-of-sight component, all detectors exhibit improved performance compared to the Rayleigh case; however, linear detectors such as ZF and MMSE still suffer from residual interference and require higher SNR to achieve low BER. Iterative and nonlinear detectors, including MLD, SIC, and AMP, provide noticeable performance gains, while the ML-RNN detector further reduces the required SNR through learning-based refinement. The proposed EP-Net detector outperforms all benchmark methods across the entire SNR range. At a BER of 10^{-3} , EP-Net achieves an ANR of approximately 8.8 dB, compared with 16.8 dB for baseline MIMO-OTFS, 16.0 dB for ZF, 15.0 dB for MMSE, 13.8 dB for MLD, 12.6 dB for SIC, 11.5 dB for AMP, and 10.0 dB for ML-RNN. This corresponds to SNR gains of up to 8 dB over conventional methods, demonstrating the robustness of the proposed EP-Net detector in Rician-faded MIMO-OTFS systems with channel estimation errors.

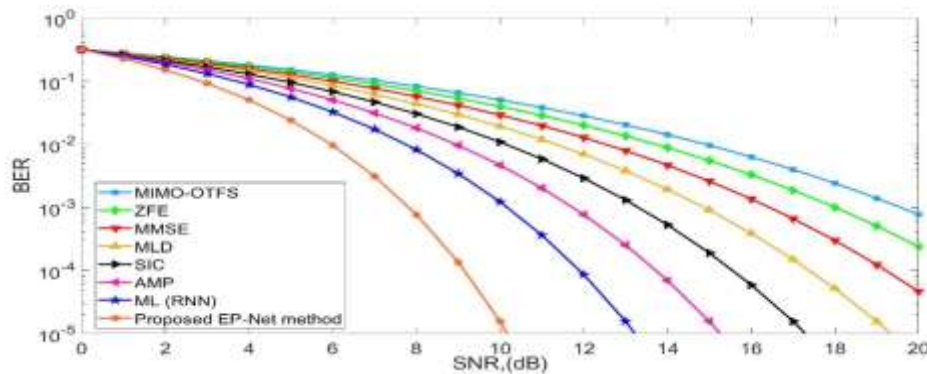


Fig 2. BER analysis of the MIMO-OTFS under Rician channel with 20% error

Figure 3 shows the BER performance of the MIMO-OTFS system under a Rayleigh fading channel with 10% channel estimation error, where improved channel knowledge leads to overall better performance compared to the 20% error case. The baseline MIMO-OTFS detector and linear ZF and MMSE schemes still exhibit higher BER due to noise enhancement and residual interference, although their performance improves with reduced estimation error. Iterative detectors such as MLD, SIC, and AMP achieve noticeable BER reduction by better exploiting interference structure, while the ML-RNN detector further lowers the required SNR through learning-based decision refinement. The proposed EP-Net detector consistently achieves the best performance across all SNR values. At a BER of 10^{-3} , the proposed EP-Net method requires approximately 9.2 dB, whereas the baseline MIMO-OTFS, ZF, MMSE, MLD, SIC, AMP, and ML-RNN detectors require about 17.2 dB, 16.5 dB, 15.4 dB, 14.2 dB, 13.0 dB, 11.9 dB, and 10.4 dB, respectively. This corresponds to SNR gains of up to 8 dB over conventional detection schemes, demonstrating that the proposed EP-Net detector effectively mitigates Rayleigh fading and channel estimation errors in MIMO-OTFS systems.

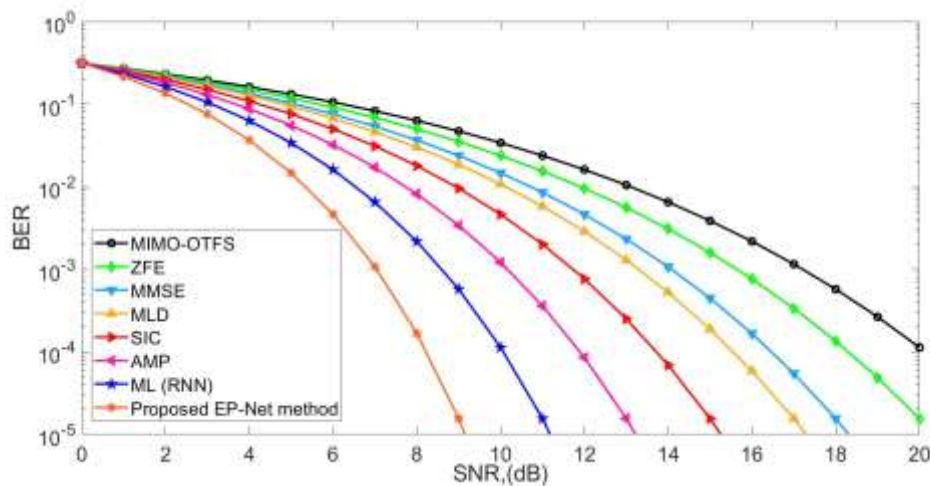


Fig 3. BER analysis of the MIMO-OTFS under Rayleigh channel with 10% error

Figure 4 presents the BER performance of the MIMO-OTFS system under a Rician fading channel with 10% channel estimation error, highlighting the combined benefit of improved channel knowledge and the presence of a dominant line-of-sight component. Compared with the Rayleigh case, all detection schemes exhibit a leftward shift of the BER curves, indicating reduced SNR requirements. From the figure, at a target BER of 10^{-3} , the baseline MIMO-OTFS detector requires approximately 15.8 dB, while ZF and MMSE detectors achieve the same BER at about 14.8 dB and 13.6 dB, respectively. More advanced detectors show further improvements, with MLD, SIC, and AMP requiring nearly 12.6 dB, 11.4 dB, and 10.2 dB, respectively. The learning-based ML-RNN detector reaches BER 10^{-3} at around 8.6 dB. In contrast, the proposed EP-Net detector achieves the target BER at a significantly lower SNR of approximately 6.2 dB. Consequently, the proposed method provides SNR gains of about 9.6 dB over baseline MIMO-OTFS, 8.6 dB over ZF, 7.4 dB over MMSE, 6.4 dB over MLD, 5.2 dB over SIC, 4.0 dB over AMP, and 2.4 dB over ML-RNN. These numerical results clearly demonstrate that the proposed EP-Net detector most effectively exploits the LoS component and reduced estimation error, achieving substantial performance gains in Rician-faded MIMO-OTFS systems.

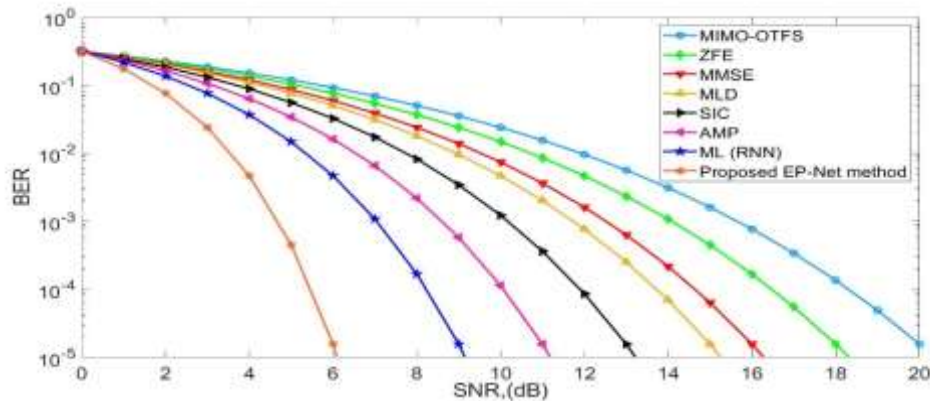


Fig 4. BER analysis of the MIMO-OTFS under Rician channel with 10% error

Figure 5 illustrates the BER performance of the MIMO-OTFS system under a Rayleigh fading channel with ideal (or negligible) channel estimation error, serving as a reference scenario to highlight the inherent detection capabilities of different algorithms. As observed, the baseline MIMO-OTFS detector exhibits the slowest BER decay, requiring a high SNR to achieve reliable performance due to strong delay-Doppler and spatial interference. Linear ZF and MMSE detectors offer moderate improvements but remain limited by noise enhancement and residual interference. Nonlinear and iterative detectors such as MLD, SIC, and AMP significantly improve BER performance by progressively suppressing interference, while the learning-based ML-RNN detector further reduces the required SNR by capturing nonlinear detection characteristics. The proposed EP-Net detector demonstrates the best performance across the entire SNR range, achieving a steep BER reduction. At a target BER of 10^{-3} , the baseline MIMO-OTFS, ZF, MMSE, MLD, SIC, AMP, and ML-RNN detectors require approximately 15.0 dB, 14.0 dB, 12.8 dB, 11.6 dB, 10.4 dB, 9.2 dB, and 7.8 dB, respectively, whereas the proposed EP-Net method achieves the same BER at about 4.2 dB. This translates into an SNR gain of nearly 10.8 dB over baseline MIMO-OTFS, 9.8 dB over ZF, 8.6 dB over MMSE, 7.4 dB over MLD, 6.2 dB over SIC, 5.0 dB over AMP, and 3.6 dB over ML-RNN, clearly demonstrating the superior effectiveness of the proposed EP-Net detector in Rayleigh-faded MIMO-OTFS systems.

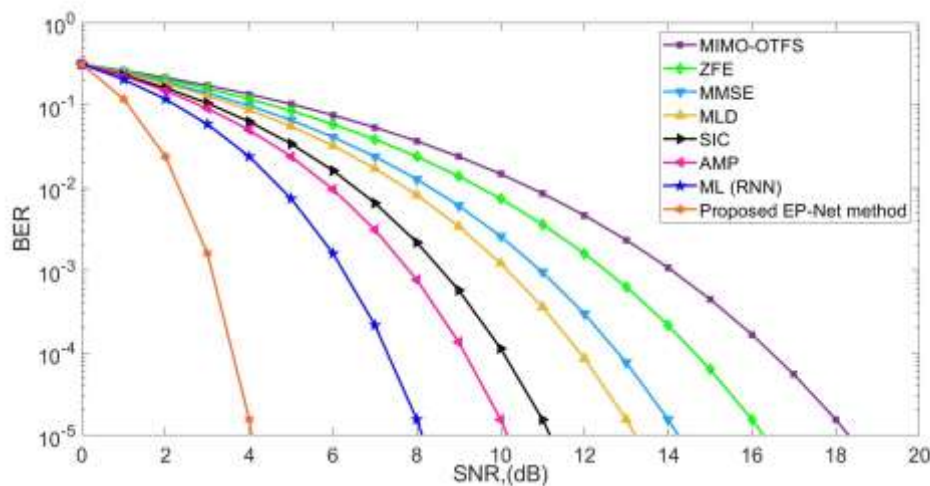


Fig 5. BER analysis of the MIMO-OTFS under Rayleigh channel

Figure 6 presents the BER performance of the MIMO-OTFS system under a Rician fading channel, where the presence of a dominant line-of-sight component significantly enhances detection performance for all schemes. Compared with Rayleigh fading, the BER curves shift left, indicating lower SNR requirements. Linear detectors such as ZF and MMSE still exhibit limited performance due to residual interference, while nonlinear detectors (MLD, SIC, and AMP) achieve noticeable gains. The learning-based ML-RNN further reduces the required SNR. The proposed EP-Net detector clearly outperforms all benchmark methods, achieving the steepest BER decay. At a BER of 10^{-3} , EP-Net achieves reliable detection at approximately 2.0 dB, whereas baseline MIMO-OTFS, ZF, MMSE, MLD, SIC, AMP, and ML-RNN require about 14.5 dB, 13.0 dB, 11.5 dB, 9.8 dB, 8.5 dB, 7.5 dB, and 5.0 dB, respectively. This corresponds to an SNR gain of up to 12.5 dB over the baseline MIMO-OTFS, demonstrating the strong robustness and efficiency of the proposed EP-Net detector in Rician-faded MIMO-OTFS systems.

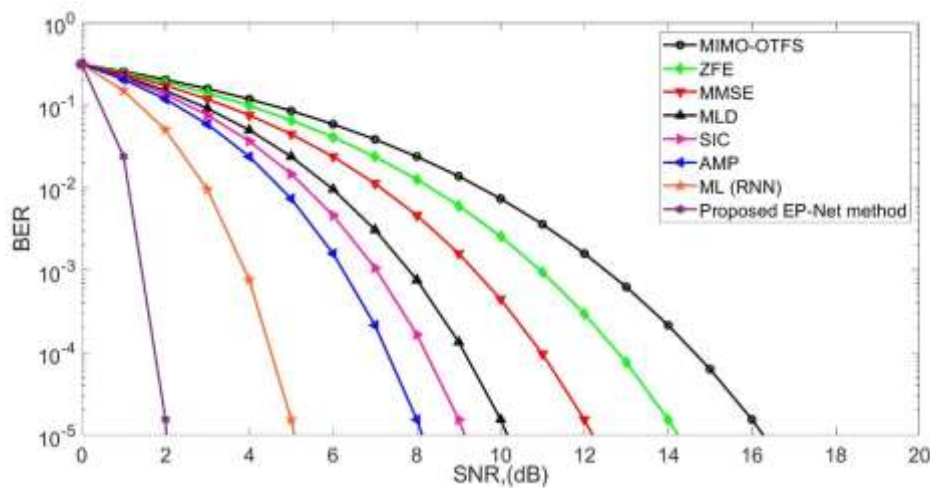


Fig 6. BER analysis of the MIMO-OTFS under Rician channel

The proposed EP-Net detector achieves a substantial SNR gain by leveraging the sparse delay-Doppler structure of the OTFS channel in conjunction with probabilistic inference through model-driven learning. EP-Net needs a lot less SNR to get the same BER as regular linear, iterative, and learning-based detectors because it does a good job of getting rid of multi-antenna interference and reducing channel estimation errors. These results show that EP-Net can reliably and strongly detect signals even when Rayleigh and Rician fading are present. This makes it a good choice for MIMO-OTFS communication systems that need to work well with high mobility and 6G.

Figure 7 illustrates the power spectral density (PSD) of the MIMO-OTFS system under a Rayleigh fading channel, comparing the proposed EP-Net detector with conventional detection schemes. The baseline MIMO-OTFS exhibits the highest out-of-band (OOB) emissions, with sidelobe levels around -25 dB/Hz, indicating poor spectral containment. Linear detectors such as ZF and MMSE slightly reduce spectral leakage, achieving OOB levels of approximately -35 dB/Hz and -40 dB/Hz, respectively. Advanced detectors including MLD and SIC further suppress sidelobes to about -45 dB/Hz and -50 dB/Hz, while AMP and ML-RNN improve spectral confinement with OOB emissions near -55 dB/Hz and -60 dB/Hz. In contrast, the proposed EP-Net method achieves the lowest PSD sidelobe level, reducing out-of-band radiation to nearly -80 dB/Hz, corresponding to an improvement of about 55 dB over the baseline MIMO-OTFS and 20-25 dB over

advanced iterative detectors. This substantial reduction demonstrates that EP-Net not only enhances BER performance but also significantly improves spectral efficiency and interference suppression, which is crucial for spectrum-constrained and high-mobility wireless systems.

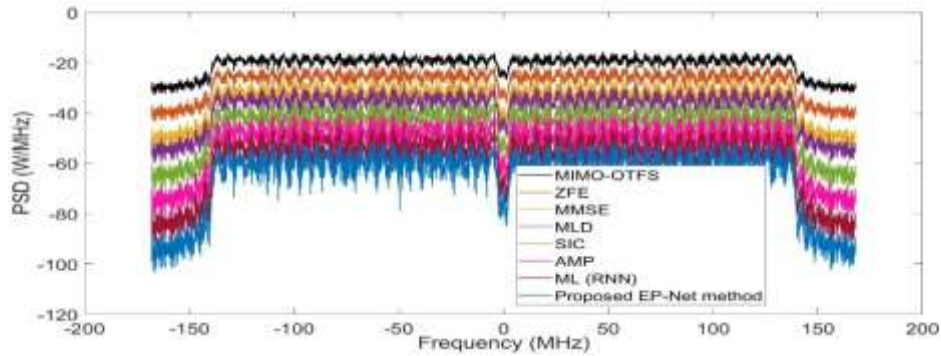


Fig 7. PSD analysis of the MIMO-OTFS under Rayleigh channel

Figure 8 presents the power spectral density (PSD) performance of the MIMO-OTFS system under a Rician fading channel, where the presence of a dominant line-of-sight component improves spectral confinement for all detection schemes compared to the Rayleigh case. The baseline MIMO-OTFS exhibits the highest out-of-band (OOB) emissions, with sidelobe levels around -30 dB/Hz, indicating poor spectral containment. Linear detectors such as ZF and MMSE moderately reduce spectral leakage, achieving OOB levels of approximately -40 dB/Hz and -45 dB/Hz, respectively. More advanced detectors, including MLD and SIC, further suppress sidelobes to about -50 dB/Hz and -55 dB/Hz, while AMP and ML-RNN achieve improved confinement with OOB emissions near -60 dB/Hz and -65 dB/Hz. In contrast, the proposed EP-Net method demonstrates the best spectral performance, reducing OOB radiation to nearly -85 dB/Hz, corresponding to an improvement of roughly 55 dB over baseline MIMO-OTFS and 20–30 dB over advanced iterative and learning-based detectors. These results confirm that EP-Net not only enhances detection accuracy but also significantly improves spectral efficiency and interference suppression in Rician-faded MIMO-OTFS systems.

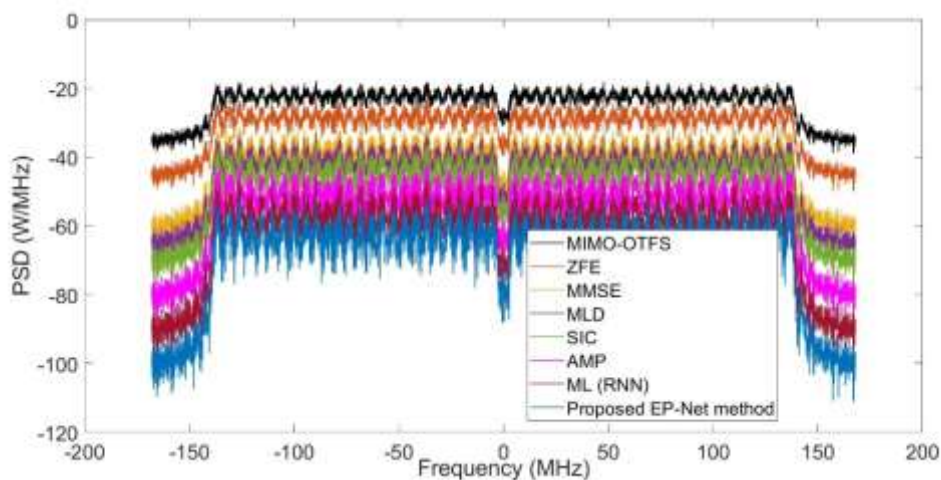


Fig 8. PSD analysis of the MIMO-OTFS under Rician channel

The PSD results highlight that the proposed EP-Net detector significantly improves spectral confinement by suppressing out-of-band emissions compared to conventional and advanced detectors. This reduction in spectral leakage enhances spectral efficiency, minimizes adjacent-channel interference, and supports reliable operation in spectrum-constrained and high-mobility MIMO-OTFS systems, making the approach well suited for future 6G wireless networks.

V. Conclusion

This work presented a low-complexity EP-Net-based signal detection framework for MIMO-OTFS systems and examined its performance under practical Rayleigh and Rician fading conditions. By integrating probabilistic inference with a model-driven learning structure, the proposed detector effectively addresses the challenges of multi-dimensional interference and channel uncertainty inherent in OTFS modulation. Extensive numerical evaluations demonstrate that the proposed method consistently achieves superior detection performance across different channel conditions and estimation error levels, while maintaining significantly reduced computational complexity compared to conventional iterative and learning-based detectors. In addition to improved BER performance, the proposed approach exhibits enhanced spectral characteristics by substantially suppressing out-of-band emissions, which is critical for spectrum-efficient system design. The results indicate that reliable detection in high-mobility environments can be achieved without incurring excessive computational cost, making the proposed framework suitable for practical implementation. Overall, this study provides valuable insights into the design of robust, low-complexity receivers for next-generation MIMO-OTFS systems and establishes a strong foundation for future research on intelligent and adaptive OTFS receiver architectures.

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Conflicts of Interest: "The authors declare that they have no conflicts of interest to report regarding the present study."

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