IEEE Open Journal of the Communications Society

Received 8 May 2023; revised 2 June 2023; accepted 23 June 2023. Date of publication 12 July 2023; date of current version 28 July 2023.

Digital Object Identifier 10.1109/OJCOMS.2023.3290542

Noncoherent SIMO Transmission via MOCZ for Short Packet-Based Machine-Type Communications in Frequency-Selective Fading Environments

YAPING SUN[1], YUFEI ZHANG[1], GAOQI DOU[1], YIKUN LU[1], AND YAN SONG[2]

[1]Department of Communication Engineering, Naval University of Engineering, Wuhan 430000, China

[2]Research Office, Army Aviation Institute, Beijing 101116, China

CORRESPONDING AUTHOR: G. DOU (e-mail: hjgcqq@163.com)

This work was supported by the National Natural Science Foundation of China under Grant 61871473 and Grant 42174051.

(Yaping Sun and Yufei Zhang are co-first authors).

ABSTRACT Massive machine type communication (mMTC) is expected to support the connections of billion devices, where a sporadic short packet transmission is a key feature for mMTC applications. Conventional pilot-based coherent schemes suffer from a huge resource overhead as the pilot occupies a large portion in the short packet transmission. To avoid the overhead and latency caused by pilot symbols and mitigate the adverse effect of wireless fading, we develop a noncoherent single-input multiple-output (SIMO) framework with modulation on conjugate-reciprocal zeros (MOCZ) for short packet transmission. A novel low-complexity noncoherent Viterbi-like detector is proposed, which can exploit diversity of receive antennas by jointly testing the zeros of the received MOCZ symbol over independent channel realizations. Simulation results demonstrate that the proposed detector can outperform the pilot-based OFDM systems and get better performance than the direct zero-testing detector for short packet transmissions in frequency-selective fading environments.

INDEX TERMS Machine type communication, short packet transmissions, single-input multiple-output (SIMO), noncoherent detection, MOCZ, frequency selective fading.

I. INTRODUCTION

Massive machine-type communications (mMTC) has been considered a great potential technology, which is expected to support tremendous Internet-of-Things (IoT) connections in future communication networks [1]. Different from the conventional human type communications, mMTC applications, adopt information as small as several bytes per packet, such as low-cost sensor nodes in IoT networks and sensor readings in healthcare, logistics, manufacturing, process automation. Such short-packet messages of sporadic characteristic dominate the future communication, which will pose new challenges for physical layer design [2]. The conventional coherent transmission schemes may introduce a long pilot symbols (delay) with a size comparable to that of short packets [3], [4], particularly in low signal-to-noise ratio (SNR) regime [5]. On the other hand, in the case of mobile wireless sensor networks, the channel may vary quickly and thus the short coherence time may lead to ineffective estimation of channel state information (CSI) at the receiver. Therefore, the framework structure of short packets needs to be redesigned and new noncoherent or blind transmission strategies suited for short packet transmission are required [6], [7].

Recently, a novel noncoherent modulation scheme, called modulation on conjugate-reciprocal zeros (MOCZ) [8], [9], [10], is proposed to transmit sporadic short packets over unknown wireless channels and completely avoids channel estimation and signal equalization at the receiver even if the data length is shorter than the channel impulse response (CIR). However, the MOCZ for short packets doesn't perform well in wireless frequency-selective fading environments, especially over deep fading channels. In fact, various diversity techniques are used to mitigate the adverse effect of wireless fading by sending the same data through

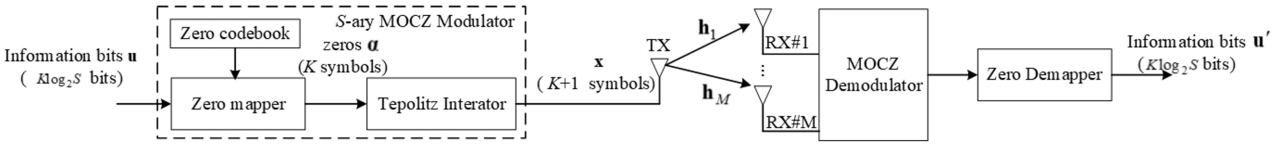


FIGURE 1. **The system model of SIMO system with MOCZ scheme.**

multiple independently fading paths. Theoretically, diversity in wireless communications can be achieved in the time, frequency, or space domains [11]. However, time diversity or frequency diversity may be costly for mMTC applications, since the enhancement of reliability is at the cost of latency or the scarce spectrum resource. Whereas the spatial diversity gains can be obtained through equipping multiple antennas at the base stations in uplink transmissions, which is hence preferable in the IoT use cases [12], especially in low SNR regime that is the case for most battery-powered industrial sensors and devices.

Motivated by the critical significance of space diversity for reliable communication within very low latency budget [12], [13], [14], we develop a noncoherent single-input multiple-output (SIMO) framework with MOCZ for short packet transmissions. This model can represent many typical mMTC use cases, whereinmultiple sensors transmit their measurements to a central controller in a TDMA manner. A novel low-complexity noncoherent Viterbi-like detector is proposed for MOCZ in SIMO system, which has much lower computational complexity than the exhaustive search method and gains better detection performance than the original Direct Zero-Testing (DiZeT) detector. The effective throughput is defined to measure the performance of different schemes for short packet communications.

II. SYSTEM MODEL

As is shown in Figure 1, we consider a SIMO system with MOCZ scheme in which a single antenna transmitter (TX) sends data symbols to a receiver (RX) equipped with M antennas. For S-ary MOCZ scheme, the information bits are modulated onto the K zeros (roots) of the z-transform (polynomial) of the consecutive samples of the time-discrete baseband signal, i.e.,

$$X(z) = \sum_{k=0}^{K} x_k z^k = x_K \prod_{k=1}^{K} (z - \alpha_k), \tag{1}$$

where the transmitted sequence $\mathbf{x} = (x_0, x_1, \ldots, x_K)^T \in \mathbb{C}^{K+1}$ denotes the coefficients of the polynomial $\mathrm{X}(z)$.

The S-ary MOCZ modulates the kth information symbol $u_k \in [0, 1, \ldots, S-1]$ onto the kth zero $\alpha_k = \alpha_k^{(u_k)}$ selected from the zero codebook $\Theta^K = \Theta_1 \times \cdots \times \Theta_K = \{\alpha_1^{(0)}, \ldots, \alpha_1^{(S-1)}\} \times \cdots \times \{\alpha_K^{(0)}, \ldots, \alpha_K^{(S-1)}\}$, where $\alpha_k^{(u_k)} = R^{(-1)^{u_k}} e^{-j2\pi(2\lfloor u_k/2\rfloor+(k-1)S)/(SK)}$ with $R = \sqrt{1 + (\log_2(2S) - 0.3)\sin(\pi/KS)}$. The zero distribution of Binary MOCZ (BMOCZ) is depicted in Figure 2.

The channel between the transmitter and the mth receiver antenna is modeled as a frequency-selective Rayleigh fading

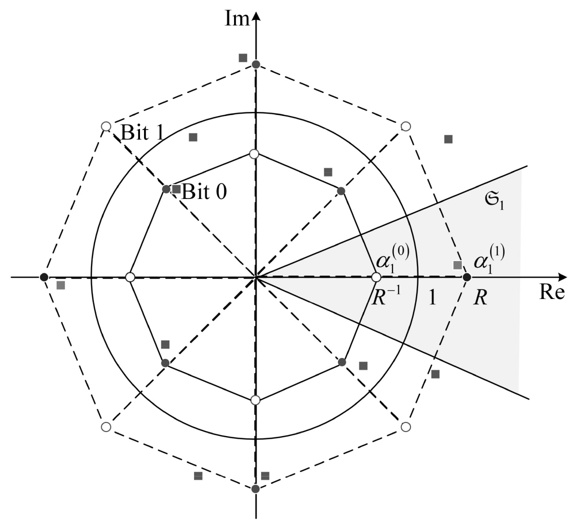


FIGURE 2. **The zero distribution of BMOCZ scheme. (The red circles denote the zero pairs from zero codebook; solid red circles denote the actual transmitted zeros while the blue squares denote the received zeros, comprised of channel zeros and data zeros.)**

channel, of which the CIR is given by $\mathbf{h}_m \in \mathbb{C}^L$, where L is the maximum length of CIR. Then the $N = K + L$ samples $\mathbf{y}_m \in \mathbb{C}^N$ for the mth receiver antenna is given by

$$\mathbf{y}_m = \mathbf{x} * \mathbf{h}_m + \mathbf{w}_m, m = 1, \ldots, M, \tag{2}$$

where $\mathbf{w}_m \in \mathbb{C}^N$ is the additive noise at the mth antenna which follows $w_m[n] \sim CN(0, N_0)$.

The convolution operation between the transmitted signal $\mathbf{x}$ and $\mathbf{h}_m$ in (2) can be transformed in z-domain as a polynomial multiplication and the received signal in (2) is given by

$$\begin{aligned} \mathrm{Y_m}(z) &= \mathrm{X}(z)\mathrm{H}_m(z) + \mathrm{W}_m(z) \\ &= x_K h_{L-1} \prod_{k=1}^{K}(z - \alpha_k) \prod_{l=1}^{L-1}(z - \beta_l) + w_{N-1} \prod_{n=1}^{N-1}(z - \gamma_n), \end{aligned} \tag{3}$$

where $\mathrm{X}(z)$, $\mathrm{H}_m(z)$, and $\mathrm{W}_m(z)$ are the polynomials of degree K, $L-1$ and $N-1$ with coefficient vectors $\mathbf{x}$, $\mathbf{h}_m$, and $\mathbf{w}_m$, respectively.

III. NONCOHERENT VITERBI-LIKE DETECTOR FOR MOCZ IN SIMO SYSTEM

The MOCZ scheme can transmit message by modulating the information bits onto the zero structure of the z-transform of the transmitted discrete-time baseband signal, and an easy separation of data zeros and channel zeros can be obtained without knowledge of the CIR realization in z-domain. However, its performance doesn't work well under frequency-selective fading channels, especially in the case where the channel may experience a deep fading condition. In such scenarios, the detection performance is heavily affected, which in turn degrades the performance of the overall system. In order to mitigate the adverse effect of the fading channel, the SIMO transmission with multiple antennas at the receiver is a feasible solution. In this section, we derive a novel low-complexity noncoherent Viterbi-like detector for the SIMO transmission with MOCZ over frequency-selective fading channels, which can not only improve the zero-detection performance as compared to DiZeT method [8] but also exploit diversity of receive antennas. This detector is different from traditional pilot-based coherent schemes, which need first to estimate the channel for each antenna to exploit diversity of receive antennas [15], [16].

A. THE MAXIMUM LIKELIHOOD (ML) DETECTION OF MOCZ

For such a SIMO system, the detection problem with maximum a posteriori (MAP) [17] rule can be formulated as

$$\begin{aligned}\widehat{\boldsymbol{\alpha}} &= \underset{\boldsymbol{\alpha}\in\Theta}{\operatorname{argmax}}\, p(\boldsymbol{\alpha}, [\mathbf{h}_1,\ldots,\mathbf{h}_M] | [\mathbf{y}_1,\ldots,\mathbf{y}_M]) \\ &\overset{(a)}{=} \underset{\boldsymbol{\alpha}\in\Theta}{\operatorname{argmax}} \frac{p([\mathbf{y}_1,\ldots,\mathbf{y}_M]|\boldsymbol{\alpha},[\mathbf{h}_1,\ldots,\mathbf{h}_M])p(\boldsymbol{\alpha})p([\mathbf{h}_1,\ldots,\mathbf{h}_M])}{p([\mathbf{y}_1,\ldots,\mathbf{y}_M])},\end{aligned} \tag{4}$$

where (a) follows from Bayes' theorem. In (4), $p(\boldsymbol{\alpha}) = \prod_{k=1}^{K} P(\alpha_k)$, where $P(\alpha_k)$ is the a priori probability of the k-th zero α_k. In the absence of a priori probability, $P(\alpha_k) = 1/2$ for all k, and therefore $p(\boldsymbol{\alpha}) = 1/2^K$ is a constant that can be omitted. Since the detector does not have the priori information about the CIR, the probability $p([\mathbf{h}_1,\ldots,\mathbf{h}_M])$ is also a constant. Besides, the received signal $[\mathbf{y}_1,\ldots,\mathbf{y}_M]$ is exactly known at the receiver and therefore $p([\mathbf{y}_1,\ldots,\mathbf{y}_M])$ represents a constant and does not affect the maximization problem. Then, the original optimization detection in (4) can be simplified as [18]

$$\widehat{\boldsymbol{\alpha}} = \underset{\boldsymbol{\alpha}\in\Theta}{\operatorname{argmax}}\, p([\mathbf{y}_1,\ldots,\mathbf{y}_M]|\boldsymbol{\alpha},[\mathbf{h}_1,\ldots,\mathbf{h}_M]). \tag{5}$$

By defining $\mathbf{x}_{K-i} = [\mathbf{0}_i, x_0, x_1, \ldots, x_K, \mathbf{0}_{N-K-i-1}]^T \in \mathbb{C}^N$ and $\mathbf{X}(\boldsymbol{\alpha}) = [\mathbf{x}_K, \mathbf{x}_{K-1}, \ldots, \mathbf{x}_{K-L+1}] \in \mathbb{C}^{N\times L}$, where $\mathbf{0}_i$ denotes a row vector containing i elements of zero, the convolution in (2) can also be compactly written as $\mathbf{y}_m = \mathbf{X}(\boldsymbol{\alpha})\mathbf{h}_m + \mathbf{w}_m,\ m = 1,\ldots,M$.

For additive white Gaussian noise (AWGN) channel, the probability of the received sequence $[\mathbf{y}_1,\ldots,\mathbf{y}_M]$ conditioned on an arbitrary sequence of transmitted zeros $\boldsymbol{\alpha}$ and the channel $[\mathbf{h}_1,\ldots,\mathbf{h}_M]$ is given by

$$\begin{aligned}&p([\mathbf{y}_1,\ldots,\mathbf{y}_M]|\boldsymbol{\alpha},[\mathbf{h}_1,\ldots,\mathbf{h}_M]) \\ &\quad= \frac{1}{(\pi N_0)^{\mathrm{NM}}} \exp\left(\sum_{m=1}^{M}\left\{-\frac{1}{N_0}\|\mathbf{y}_m - \mathbf{X}(\boldsymbol{\alpha})\mathbf{h}_m\|^2\right\}\right).\end{aligned} \tag{6}$$

With $[\mathbf{h}_1,\ldots,\mathbf{h}_M]$, the ML detector can be given by

$$\widehat{\boldsymbol{\alpha}}_{ML} = \underset{\boldsymbol{\alpha}\in\Theta}{\operatorname{argmin}} \sum_{m=1}^{M}\left\{\|\mathbf{y}_m - \mathbf{X}(\boldsymbol{\alpha})\mathbf{h}_m\|^2\right\}. \tag{7}$$

However, the receiver has no knowledge of the CSI, it has to be marginalized out for noncoherent detection. Supposing that the receiver knows the transmitted zero sequence $\boldsymbol{\alpha}$, the CSI can be obtained as a closed-form solution [19] for

$$\begin{aligned}&\left[\mathbf{h}_1^{ML}(\boldsymbol{\alpha}),\ldots,\mathbf{h}_M^{ML}(\boldsymbol{\alpha})\right] = \underset{[\mathbf{h}_1,\ldots,\mathbf{h}_M]\in\mathbb{C}^{L\times M}}{\operatorname{argmin}} \sum_{m=1}^{M}\left\{\|\mathbf{y}_m - \mathbf{X}(\boldsymbol{\alpha})\mathbf{h}_m\|^2\right\} \\ &= \left[\left(\mathbf{X}^H(\boldsymbol{\alpha})\mathbf{X}(\boldsymbol{\alpha})\right)^{-1}\mathbf{X}^H(\boldsymbol{\alpha})\mathbf{y}_1,\ldots,\left(\mathbf{X}^H(\boldsymbol{\alpha})\mathbf{X}(\boldsymbol{\alpha})\right)^{-1}\mathbf{X}^H(\boldsymbol{\alpha})\mathbf{y}_M\right]\end{aligned} \tag{8}$$

To obtain the decision rule of the noncoherent detector, the channel $[\mathbf{h}_1,\ldots,\mathbf{h}_M]$ in (7) is replaced by $[\mathbf{h}_1^{ML}(\boldsymbol{\alpha}),\ldots,\mathbf{h}_M^{ML}(\boldsymbol{\alpha})]$ and the maximum likelihood (ML) detection is given by

$$\widehat{\boldsymbol{\alpha}}_{ML} = \underset{\boldsymbol{\alpha}\in\Theta}{\operatorname{argmin}} \sum_{m=1}^{M}\left\{\left\|\mathbf{y}_m - \mathbf{X}(\boldsymbol{\alpha})\mathbf{h}_m^{ML}(\boldsymbol{\alpha})\right\|^2\right\}, \tag{9}$$

where $[\mathbf{h}_1^{ML}(\boldsymbol{\alpha}),\ldots,\mathbf{h}_M^{ML}(\boldsymbol{\alpha})]$ is the ML estimate of the SIMO channel under the assumption that $\boldsymbol{\alpha}$ was actually transmitted.

By discarding the constant terms and substituting (8) in (9), the ML problem is given by

$$\begin{aligned}\widehat{\boldsymbol{\alpha}}_{ML} &= \underset{\boldsymbol{\alpha}\in\Theta}{\operatorname{argmax}} \sum_{m=1}^{M} \mathbf{y}_m^H\mathbf{X}(\boldsymbol{\alpha})\mathbf{h}_m^{ML}(\boldsymbol{\alpha}) \\ &= \underset{\boldsymbol{\alpha}\in\Theta}{\operatorname{argmax}} \sum_{m=1}^{M} \mathbf{y}_m^H\mathbf{X}(\boldsymbol{\alpha})\left(\mathbf{X}^H(\boldsymbol{\alpha})\mathbf{X}(\boldsymbol{\alpha})\right)^{-1}\mathbf{X}^H(\boldsymbol{\alpha})\mathbf{y}_m.\end{aligned} \tag{10}$$

The orthogonal projector of a vector $\mathbf{y}_m \in \mathbb{C}^N$ onto $\mathbf{X}(\boldsymbol{\alpha}) \in \mathbb{C}^{N\times L}$ and $\mathbf{V}_\alpha \in \mathbb{C}^{N\times K}$ can be denoted as $\mathbf{X}(\boldsymbol{\alpha})(\mathbf{X}^H(\boldsymbol{\alpha})\mathbf{X}(\boldsymbol{\alpha}))^{-1}\mathbf{X}^H(\boldsymbol{\alpha})\mathbf{y}_m$ and $\mathbf{V}_\alpha(\mathbf{V}_\alpha^H\mathbf{V}_\alpha)^{-1}\mathbf{V}_\alpha^H\mathbf{y}_m$ respectively, where $\mathbf{V}_\alpha$ is the left null space of $\mathbf{X}(\boldsymbol{\alpha})$ and $\operatorname{rank}(\mathbf{X}) + \operatorname{rank}(\mathbf{V}_\alpha) = L + K = N$. Hence according to orthogonal projection theorem, we can get $\mathbf{y}_m = \mathbf{X}(\boldsymbol{\alpha})(\mathbf{X}^H(\boldsymbol{\alpha})\mathbf{X}(\boldsymbol{\alpha}))^{-1}\mathbf{X}^H(\boldsymbol{\alpha})\mathbf{y}_m + \mathbf{V}_\alpha(\mathbf{V}_\alpha^H\mathbf{V}_\alpha)^{-1}\mathbf{V}_\alpha^H\mathbf{y}_m$.

Indeed, $\mathbf{V}_\alpha$ is provided by the Vandermonde matrix generated by the zero vector $\boldsymbol{\alpha}$ of $X(z)$

$$\begin{aligned}\mathbf{V}_\alpha^H &= \begin{pmatrix} 1 & \alpha_1 & \alpha_1^2 & \cdots & \alpha_1^{N-1} \\ 1 & \alpha_2 & \alpha_2^2 & \cdots & \alpha_2^{N-1} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & \alpha_K & \alpha_K^2 & \cdots & \alpha_K^{N-1}\end{pmatrix} \\ &\Rightarrow \mathbf{V}_\alpha^H\mathbf{X}(\boldsymbol{\alpha}) = \mathbf{0}_{K\times L} \text{ and } \mathbf{X}^H(\boldsymbol{\alpha})\mathbf{V}_\alpha = \mathbf{0}_{L\times K}.\end{aligned} \tag{11}$$

Then, the optimal estimates of the transmitted zeros using the noncoherent ML detector can be rewritten as [8]

$$\widehat{\boldsymbol{\alpha}}_{ML} = \underset{\boldsymbol{\alpha}\in\Theta}{\operatorname{argmax}} \sum_{m=1}^{M} \mathbf{y}_m^H\mathbf{X}(\boldsymbol{\alpha})\left(\mathbf{X}^H(\boldsymbol{\alpha})\mathbf{X}(\boldsymbol{\alpha})\right)^{-1}\mathbf{X}^H(\boldsymbol{\alpha})\mathbf{y}_m$$

$$= \underset{\boldsymbol{\alpha}\in\Theta}{\operatorname{argmax}} \sum_{m=1}^{M} \left(\mathbf{y}_m^H \left(I_N - \mathbf{V}_\alpha \left(\mathbf{V}_\alpha^H \mathbf{V}_\alpha \right)^{-1} \mathbf{V}_\alpha^H \right) \mathbf{y}_m \right)$$

$$= \underset{\boldsymbol{\alpha}\in\Theta}{\operatorname{argmin}} \sum_{m=1}^{M} \left(\mathbf{y}_m^H \mathbf{V}_\alpha \left(\mathbf{V}_\alpha^H \mathbf{V}_\alpha \right)^{-1} \mathbf{V}_\alpha^H \mathbf{y}_m \right). \quad (12)$$

B. THE NONCOHERENT VITERBI-LIKE DETECTOR FOR MOCZ

The ML sequence detector needs to exploit exhaustive search method to maximize (12) for all the possible transmitted zero-vector $\boldsymbol{\alpha} \in \Theta^K$, which thus leads to exponential computational complexity that is proportional to S^K.

To reduce computational complexity, the Direct Zero-Testing (DiZeT) detector is proposed in [8], which approximates $(\mathbf{V}_{\boldsymbol{\alpha}}^H \mathbf{V}_{\boldsymbol{\alpha}})^{-1/2}$ in (12) with a diagonal matrix to simplify the search to independent decisions over each zero.

However, the DiZeT method ignores the correlation and simplifies (12) to independent zero decisions, which results in non-negligible performance degradation, especially for frequency-selective fading channels.

To improve the detection performance with moderate computational complexity for MOCZ, we propose a low-complexity noncoherent Viterbi-like detector and the search given by (12) can be efficiently solved with the help of Viterbi-like algorithms that operate on an appropriately defined trellis.

In the trellis, α_k denotes the current zero at time k and α_{k-1} denotes the last zero at time k–1. The state α_k can be mapped to a whole number using the mapping function

$$\alpha_k = \alpha_k^{(s)} \rightarrow s \in \mathcal{S} = \{0, 1, 2, \ldots, S-1\}. \quad (13)$$

Using (13), the trellis branch metric can be written as

$$\delta_k(s', s) = \Gamma_k(s) - \Gamma_{k-1}(s'), \quad (14)$$

where $s', s \in \mathcal{S}$ represent the starting and terminating states in a trellis transition, mapping to $\alpha_{k-1}^{(s')}$ and $\alpha_k^{(s)}$ respectively. In (14), $\Gamma_k(s)$ is the path metric at the state s, which is defined as

$$\Gamma_k(s) = \sum_{m=1}^{M} \left(\mathbf{y}_m^H \mathbf{V}_{\boldsymbol{\alpha}_k} \left(\mathbf{V}_{\boldsymbol{\alpha}_k}^H \mathbf{V}_{\boldsymbol{\alpha}_k} \right)^{-1} \mathbf{V}_{\boldsymbol{\alpha}_k}^H \mathbf{y}_m \right), \quad (15)$$

where $\boldsymbol{\alpha}_k = [\psi_{k-1}^{s'} \ \alpha_{k-1}^{(s')} \ \alpha_k^{(s)}]$, $s' \in \mathcal{S}$ represents the zero path at state s at time k, and $\psi_{k-1}^{s'} = [\widetilde{\alpha}_1 \ \widetilde{\alpha}_2 \ \cdots \ \widetilde{\alpha}_{k-3} \ \widetilde{\alpha}_{k-2}]$ represents the surviving zero sequence at state s' at time k–1. $\mathbf{V}_{\boldsymbol{\alpha}_k}^H$ can be denoted as

$$\mathbf{V}_{\boldsymbol{\alpha}_k}^H = \begin{pmatrix} 1 & \widetilde{\alpha}_1 & \widetilde{\alpha}_1^2 & \cdots & \widetilde{\alpha}_1^{N-1} \\ 1 & \widetilde{\alpha}_2 & \widetilde{\alpha}_2^2 & \cdots & \widetilde{\alpha}_2^{N-1} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & \widetilde{\alpha}_{k-2} & \widetilde{\alpha}_{k-2}^2 & \cdots & \widetilde{\alpha}_{k-2}^{N-1} \\ 1 & \alpha_{k-1}^{(s')} & \left(\alpha_{k-1}^{(s')}\right)^2 & \cdots & \left(\alpha_{k-1}^{(s')}\right)^{N-1} \\ 1 & \alpha_k^{(s)} & \left(\alpha_k^{(s)}\right)^2 & \cdots & \left(\alpha_k^{(s)}\right)^{N-1} \end{pmatrix}. \quad (16)$$

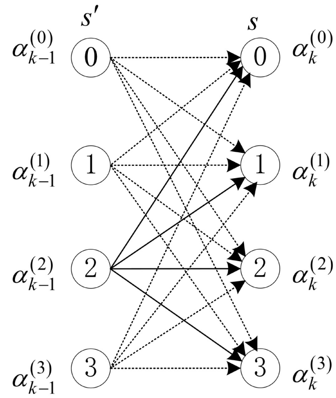


FIGURE 3. The defined trellis at time k–1 and k.

The algorithm contains three steps: cumulative metric calculating, comparing, and survivor updating. The formal definitions of the three mentioned steps are given in the following.

The algorithm first evaluates the S cumulative metric candidates $\beta_k^{s'}(s)$, $s' \in \mathcal{S}$ corresponding to the S paths terminating in state s with transitions from state s' respectively. $\beta_k^{s'}(s)$ is formally defined by

$$\beta_k^{s'}(s) = \beta_{k-1}(s') + \delta_k(s', s), \ \ s' \in \mathcal{S}, \quad (17)$$

where $\beta_{k-1}(s')$ is the accumulated metric of the surviving path at state s' at time k-1.

At comparing stage, we select the cumulative metric at each state by

$$\widetilde{s'} = \underset{s'\in\mathcal{S}}{\operatorname{argmin}} \ \beta_k^{s'}(s), \quad \beta_k(s) = \beta_k^{\widetilde{s'}}(s), \quad (18)$$

and update the corresponding surviving sequence $\psi_k^s = [\psi_{k-1}^{\widetilde{s'}} \ \alpha_{k-1}^{(\widetilde{s'})}]$. In Figure 3, the solid path denotes the corresponding surviving sequence at each state at time k.

Finally, we select the path with the minimum metric and output the zero sequence of the selected path at the last K stage.

IV. NUMERICAL SIMULATIONS

A. COMPARISON OF COMPUTATIONAL COMPLEXITY

Three methods can be used to solve (12): the exhaustive search method, the proposed method in Section III, and the DiZeT method [8]. The exhaustive search method leads to large computational complexity which is proportional to S^K, since it needs to compute and compare the value of (12) for all the possible transmitted zero sequences. The DiZeT method simplifies the exhaustive search by approximating $(\mathbf{V}_\alpha^H \mathbf{V}_\alpha)^{-1}$ to a diagonal matrix, which results in non-negligible performance degradation. The proposed method can make a good balance between complexity and performance. The computational complexity comparison is shown in Table 1.

TABLE 1. The comparison of the computational complexity of different detectors.

Method	Computational complexity
The exhaustive search method	$O\left(\left(2NK^2+2NK+K^3+N\right)S^K\right)$
The proposed detector	$O\left(\left(\frac{K(K+1)(2K+1)N}{3}+(K+3)(K-1)N+\frac{K^2(K+1)^2}{4}-1\right)S^2 + (5N+1)S\right)$
The DiZeT detector	$O(NSK)$

TABLE 2. Simulation parameters.

	MOCZ, Viterbi-like	MOCZ, DiZeT	OFDM, Known CSI	OFDM, Pilot-based
Information Bits K	32	32	32	32
Modulation	BMOCZ	BMOCZ	QPSK	QPSK
CP Length	0	0	L-1	L-1
Training Length L_p	0	0	16	16
Transmitted Sequence Length	33	33	32+L-1	32+L-1

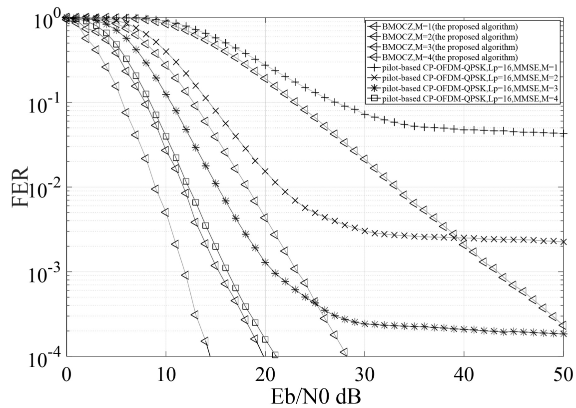


FIGURE 4. FER performance comparison versus E_b/N_0 with M=(1, 2, 3, 4).

B. CALCULATION OF EFFECTIVE THROUGHPUT

We use the effective throughput to measure the performance of different schemes for short packet transmissions. For S-ary MOCZ, when $K\log_2 S$ information bits are transmitted, only $K+1$ consecutive samples of the transmitted sequence are used for noncoherent detection, which captures the corresponding physical-layer transmission latency measured in channel uses. For pilot-based short packet transmission, the pilot length L_p with $L_p \geq L$ is allocated to acquire the CSI, which yields a significant rate loss. And pilot overhead needs to be considered when the scheme is evaluated. Hence, for a fair comparison, we refer to the effective throughput definition from [20], which is used to measure the average effectively transmitted information bits per channel used under a given detection performance, such as Frame error rate (FER). The effective throughput T can be formulated as

$$T = R_{eff}(1 - FER), \tag{19}$$

where R_{eff} is the effective rate of the scheme. For S-ary MOCZ, $R_{eff} = K\log_2 S/(K+1)$.

C. PERFORMANCE COMPARISON

1) SIMULATION SETUP

In this section, we provide simulation results to examine the performance of the noncoherent SIMO system exploiting the noncoherent Viterbi-like detector proposed in Section III (denoted as 'MOCZ, Viterbi-like') and compare it with the SIMO system using DiZeT detector (denoted as 'MOCZ, DiZeT') and pilot-based schemes. In all simulations, the number of information bits is set to K=32 and a frequency-selective fading channel with L-independent paths is considered.

The FER performance and effective throughput of the proposed MOCZ scheme are compared with that of the MOCZ scheme using DiZeT detector. We also provide the performance of the pilot-based cyclic prefix (CP) OFDM system using QPSK modulation with perfect channel knowledge (denoted as 'OFDM, Known CSI') as well as with pilot-based channel estimation (denoted as 'OFDM, Pilot-based'), where in the former, the channel is assumed to be perfectly known, and in the latter, a minimum-mean-squared-error (MMSE) estimator [21] is adopted using 16 pilot tones. A frequency selective Rayleigh fading channel with L=8 taps is considered, in which each tap has a uniform power-delay-profile, i.e., $h_m[l] \sim \mathrm{CN}(0, 1/8)$ for $l = 1, 2, \ldots, 8$. The simulation parameters are listed in Table 2.

2) SIMULATION RESULTS

Figure 4 shows the FER performance versus E_b/N_0 with M=(1, 2, 3, 4). We can observe that the proposed Viterbi-like detector achieves a better performance by increasing the number of the receive antennas. This result shows that the proposed detector can gain the diversity reception in a SIMO scenario for reliable short packet communications. In Figure 5, we provide the performance comparison for different schemes. It can be seen that the proposed noncoherent Viterbi-like detector outperforms the DiZeT detector by about 1.3 dB and obtains about 4.5 dB gain compared to the pilot-based OFDM scheme with M=4 at FER $= 10^{-3}$. What's more, since the proposed detector does not need channel estimation, it largely reduces the computational complexity required at the receiver.

Figure 6 shows the effective throughput versus E_b/N_0. It can be seen that the effective throughput of the proposed detection scheme increases as E_b/N_0 grows. Besides, the performance outperforms that of the pilot-based scheme

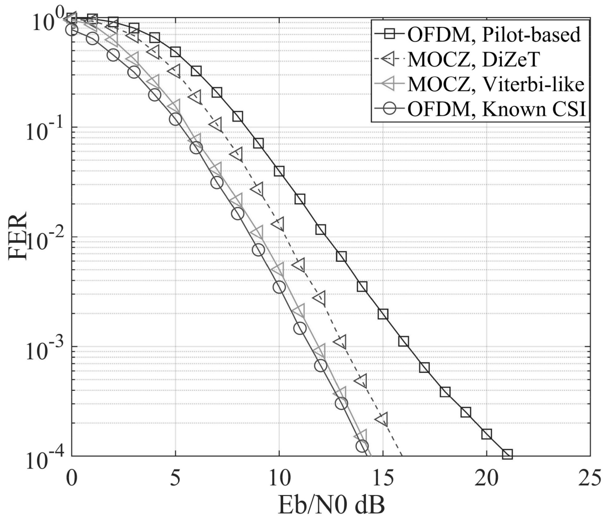


FIGURE 5. FER performance comparison for different schemes versus E_b/N_0 with M=4.

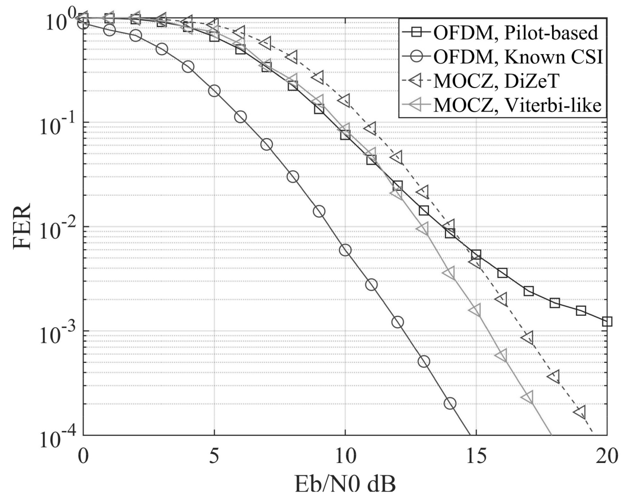


FIGURE 7. FER performance comparison versus E_b/N_0 for realistic multi-path channels when M=4.

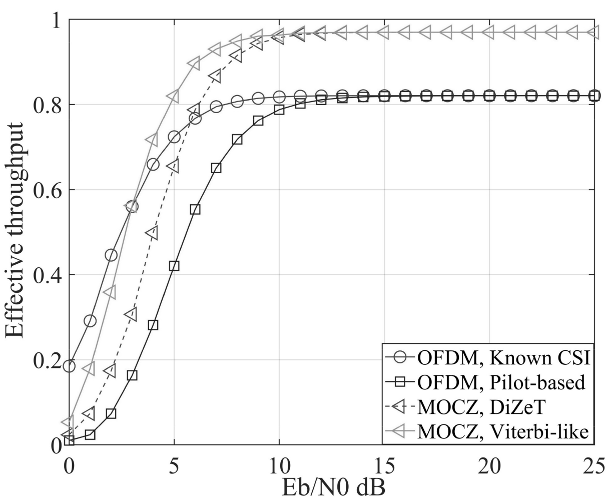


FIGURE 6. Effective throughput performance comparison versus E_b/N_0.

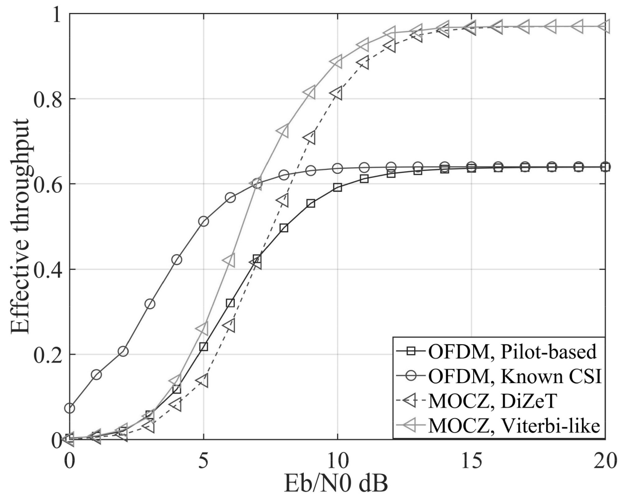


FIGURE 8. Effective throughput performance comparison versus E_b/N_0 for realistic multi-path channels when M=4.

and exhibits remarkably higher effective throughput, which validates the effectiveness of the proposed scheme. The reason is that for the pilot-based scheme the effective rate is $R_{OFDM-QPSK} = K/(K/2 + L - 1 + L_p)$, which appears as the effective throughput floor, leading to a gap of 0.1492 bits/channel use.

To further investigate the performance for more realistic multi-path channels, we used the 3GPP standardized power delay profiles Pedestrian B (PB) model, defined in [22]. The sampling rate is set to 5MHz, and thus PB will give rise to 6 multi-paths and hence becomes frequency-selective fading channel. In addition, the maximum length of CIR for PB is 19. We provide the FER and effective throughput performance for SIMO with M=4 over PB in Figure 7 and Figure 8, respectively. It can be observed that the proposed low-complexity Viterbi-like detector outperforms the conventional approach by about 1.5 dB at $FER = 10^{-3}$ and achieves better performance than the coherent scheme when $E_b/N_0 > 11$ dB. Besides, we can observe that the pilot-based scheme deteriorates rapidly due to the fact that the true CIR length is larger than the pilot length $L_p = 16$, whereas our proposed noncoherent scheme still works well in this case. What's more, it is evident in Figure 8 that the proposed method exhibits remarkably higher effective throughput than the conventional method and the coherent scheme, which means that the proposed method can transmit more information bits per channel use effectively.

V. CONCLUSION

In this paper, we develop a SIMO framework via MOCZ for short packet communications in frequency-selective fading environments and propose a noncoherent Viterbi-like detector for MOCZ, which exploits diversity of M receive antennas, by jointly testing the zeros of the received MOCZ symbol over independent channel realizations. Simulation results showed that the proposed scheme performs better with the use of multiple antennas and provides performance gains in both FER and effective throughput as compared to the conventional pilot-based OFDM schemes for short packet communications.

REFERENCES

[1] J. Choi, J. Ding, N.-P. Le, and Z. Ding, "Grant-free random access in machine-type communication: Approaches and challenges," *IEEE Wireless Commun.*, vol. 29, no. 1, pp. 151–158, Feb. 2022, doi: 10.1109/mwc.121.2100135.

[2] N. H. Mahmood et al., "White paper on critical and massive machine type communication towards 6G," 2020, *arXiv:2004.14146*.

[3] S. Dörner, J. Clausius, S. Cammerer, and S. T. Brink, "Learning joint detection, equalization and decoding for short-packet communications," *IEEE Trans. Wireless Commun.*, vol. 71, no. 2, pp. 837–850, Feb. 2023, doi: 10.1109/TCOMM.2022.3228648.

[4] X. Zhang, D. Zhang, B. Shim, G. Han, D. Zhang, and T. Sato, "Sparse superimposed coding for short-packet URLLC," *IEEE Internet Things J.*, vol. 9, no. 7, pp. 5275–5289, Apr. 2022, doi: 10.1109/JIOT.2021.3108161.

[5] B. Lee, S. Park, D. J. Love, H. Ji, and B. Shim, "Packet structure and receiver design for low latency wireless communications with ultra-short packets," *IEEE Trans. Commun.*, vol. 66, no. 2, pp. 796–807, Feb. 2018, doi: 10.1109/TCOMM.2017.2755012.

[6] R. B. D. Renna and R. C. D. Lamare, "Iterative list detection and decoding for massive machine-type communications," *IEEE Trans. Commun.*, vol. 68, no. 10, pp. 6276–6288, Oct. 2020, doi: 10.1109/TCOMM.2020.3007525.

[7] C. Xu et al., "Sixty years of coherent versus non-coherent tradeoffs and the road from 5G to wireless futures," *IEEE Access*, vol. 7, pp. 178246–178299, 2019, doi: 10.1109/ACCESS.2019.2957706.

[8] P. Walk, P. Jung, and B. Hassibi, "MOCZ for blind short-packet communication: Basic principles," *IEEE Trans. Wireless Commun.*, vol. 18, no. 11, pp. 5080–5097, Nov. 2019, doi: 10.1109/TWC.2019.2932668.

[9] P. Walk and W. Xiao, "Multi-user MOCZ for mobile machine type communications," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Nanjing, China, May 2021, pp. 1–6, doi: 10.1109/WCNC49053.2021.9417481.

[10] Y. Sun, G. Dou, H. Wang, and Y. Zhang, "Noncoherent demodulation and decoding via polynomial zeros modulation for pilot-free short packet transmissions over multipath fading channels," *IEICE Trans. Commun.*, vol. E106-B, no. 3, pp. 213–220, Mar. 2023, doi: 10.1587/Transcom.2022EBP3034.

[11] D. Tse and P. Viswanath, "Point-to-point communication: Detection, diversity and channel uncertainty," in *Fundamentals of Wireless Communication*. Cambridge, U.K.: Cambridge Univ. Press, 2005, pp. 59–101.

[12] C. Li, N. Yang, and S. Yan, "Optimal transmission of short-packet communications in multiple-input single-output systems," *IEEE Trans. Veh. Technol.*, vol. 68, no. 7, pp. 7199–7203, Jul. 2019, doi: 10.1109/tvt.2019.2917080.

[13] H. Xie, W. Xu, H. Q. Ngo, and B. Li, "Non-coherent massive MIMO systems: A constellation design approach," *IEEE Trans. Wireless Commun.*, vol. 19, no. 6, pp. 3812–3825, Jun. 2020, doi: 10.1109/TWC.2020.2978806.

[14] G. Durisi, T. Koch, and P. Popovski, "Toward massive, ultrareliable, and low-latency wireless communication with short packets," *Proc. IEEE*, vol. 104, no. 9, pp. 1711–1726, Sep. 2016, doi: 10.1109/JPROC.2016.2537298.

[15] A. Lancho, J. Östman, and G. Durisi, "On joint detection and decoding in short-packet communications," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2021, pp. 1–6, doi: 10.1109/GLOBECOM46510.2021.9685448.

[16] E. de Carvalho, E. Björnson, J. H. Sørensen, E. G. Larsson, and P. Popovski, "Random pilot and data access in massive MIMO for machine-type communications," *IEEE Trans. Wireless Commun.*, vol. 16, no. 12, pp. 7703–7717, Dec. 2017, doi: 10.1109/TWC.2017.2748106.

[17] I. Nevat, A. Wiesel, J. Yuan, and Y. C. Eldar, "Maximum a-posteriori estimation in linear models with a Gaussian model matrix," in *Proc. 41st Annu. Conf. Inf. Sci. Syst.*, 2007, pp. 63–67, doi: 10.1109/CISS.2007.4298274.

[18] X. Zhu and R. D. Murch, "Performance analysis of maximum likelihood detection in a MIMO antenna system," *IEEE Trans. Commun.*, vol. 50, no. 2, pp. 187–191, Feb. 2002, doi: 10.1109/26.983313.

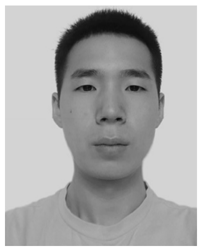
[19] M. El Xhamaa and B. Lankl, "Noncoherent symbol detection of short CPM bursts in frequency-selective fading channels," *IEEE Trans. Wireless Commun.*, vol. 19, no. 2, pp. 771–782, Feb. 2020, doi: 10.1109/TWC.2019.2948595.

[20] S. He and J. K. Tugnait, "On doubly selective channel estimation using superimposed training and discrete prolate spheroidal sequences," *IEEE Trans. Signal Process.*, vol. 56, no. 7, pp. 3214–3228, Jul. 2008, doi: 10.1109/TSP.2008.919639.

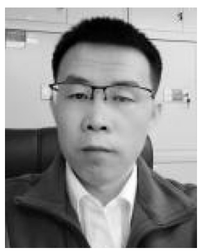
[21] Y. S. Cho, J. Kim, W. Y. Yang, and C. G. Kang, "Channel estimation," in *MIMO-OFDM Wireless Communications with MATLAB*. Singapore: Wiley, 2010, pp. 187–207.

[22] *E-UTRA User Equipment (UE) Radio Transmission and Reception, Version 16.0.0*, 3GPP Standard TS 36.101, Dec. 2018. [Online]. Available: https://itectec.com/archive/3gpp-specification-ts-36-101

YAPING SUN received the Bachelor of Engineering degree from the Naval University of Engineering in 2016, where she is currently pursuing the master's degree. Her research interests include wireless communications, channel coding, and short block communications.



YUFEI ZHANG received the Bachelor of Engineering degree from the Naval University of Engineering in 2018. His current research interests include wireless communications theory and systems.



GAOQI DOU received the B.S. and Ph.D. degrees in communication engineering from the Naval University of Engineering, Wuhan, China, in 2004 and 2009, respectively. His current research interests include the Internet of Things, wireless communication theory, information theory, electronic warfare, and software-defined radio systems.

YIKUN LU received the bachelor's degree from Nanchang University in 2016, and the master's degree from the Department of Communication Engineering, Wuhan Naval Engineering University in 2019. His research interests include wireless communication theory, software radio, and information theory.

YAN SONG received the master's degree from the Beijing University of Aeronautics and Astronautics in 2013. Her research interests include system simulation and complexity analysis.