AN ADAPTIVE LOW-COMPLEXITY DETECTION METHOD FOR STATISTICAL SIGNAL TRANSMISSION UNDER TIME-VARYING CHANNELS

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ABSTRACT

Based on orthogonal frequency division multiplexing (OFDM) systems, an additional individual data transmission can be established in statistical spectrum domain, which can be adopted for specific applications. However, the performance of existing detection methods for this kind of transmission will be severely restricted when the channel coefficients are dynamic within each observation window. In this paper, we propose an adaptive detection method for statistical signal transmission. This method has adequate adaptability for different channel varying rates, while maintaining low complexity. Simulation results show that the proposed method achieves significant performance gain compared to the original method under time varying channels.

Index Terms— Statistical signal transmission, cyclic delay diversity, orthogonal frequency division multiplexing, time-varying channel.

1. INTRODUCTION

Cyclostationary features have been widely used in multiple wireless communication applications. For example, they can be exploited in signal detection and classification under various scenarios [1, 2]. Besides, Cyclostationary features can also be used for collaborative sensing and energy-efficiency [3, 4]. Other applications in network coordination and dynamic spectrum access are discussed in [5, 6].

In [7], cyclostationary features were first adopted for signal transmission in the *statistical spectrum domain* (SS domain), which is built on OFDM systems with cyclic delay diversity (CDD) techniques. In such systems, the data stream in SS domain can be inserted into OFDM signals by artificially regulating the corresponding cyclic delays (see Fig. 1). A most compelling advantage of this technique is that the transmission in SS domain is entirely independent from the transmission of the original OFDM signals [7]. That is, it explores a parallel domain of degrees of freedom, and thus does not affect the overall spectral efficiency of the original OFDM system. Afterwards, [8] provides a cyclostationary-based implicit channel for cognitive radio systems, as an attempt for using this kind of technique at practical communication applications.

However, one drawback of the signal transmission in SS domain lies in its signal detector, which is highly complex and well beyond the computational capacity of current hardware. To combat such practical limitation, a low-complexity detection method was proposed in [9] and demonstrated to perform well, which facilitates the applications for statistical signal transmission. Nevertheless, one critical assumption in [9] is that the channel coefficients are static within the observation window of L OFDM symbols, while we found that the performance of this method degrades significantly when channel coefficients are dynamic within each observation window.

In this paper, an adaptive detection method is proposed, which contains the capability to fit different channel varying rates. Our discussion is mainly based on two hypothetical scenarios, namely scenario A and scenario B, in which the channel coefficients are static and dynamic within the observation window, respectively. We demonstrate that our method can achieve a satisfactory performance in time-varying channels, unlike the original method, which suffers serious performance degradation. Furthermore, we manifest that the method in [9] can be classified as a special case of the adaptive method.

2. SYSTEM MODEL

A typical transmitter architecture for data transmission in the SS domain is depicted in Fig. 1. Assuming N_T transmitting antennas exist in total, then at antenna n_T ($n_T \in \{1, 2, \cdots, N_T\}$), after OFDM modulation and before cyclic prefix (CP) insertion, data symbols are *cyclically shifted* ac-

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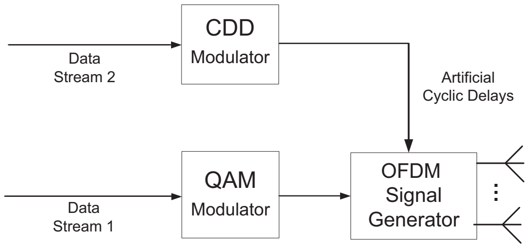

Fig. 1. A typical transmitter architecture for data transmission in the SS domain.

cording to the cyclic delays $\Delta_{n_T} \in \{\Delta_1, \Delta_2, \cdots, \Delta_{N_T}\}$, where $\Delta_1 = 0$ (see [7]). The transmitted OFDM signals at antenna n_T can be described as

$$s_{n_T}(n) = \frac{1}{\sqrt{N_T N}} \cdot \sum_{m=-\infty}^{+\infty} p(n-mM) \sum_{k=0}^{N-1} \alpha_{m,k} W_N^{k\Delta_{n_T}} W_N^{k((m+1)M-n)}, \quad (1)$$

where $W_N = e^{\frac{-j2\pi}{N}}$, N denotes the FFT size, $M = N+$CP length, $\alpha_{m,k}$ is the data of the m-th symbol and k-th subcarrier of OFDM signals, and

$$p(n) = \begin{cases} 1 & n = 0, 1, \ldots, M-1 \\ 0 & \text{otherwise} \end{cases}. \quad (2)$$

Assuming that single receiving antenna is used and letting $\mathbf{h}_l = [h_1(l), h_2(l), \cdots, h_{N_T}(l)]$ denote the discrete-time impulse response of channel, the received signal can be then written as

$$r(n) = \sum_{l=0}^{\mathcal{L}-1} \mathbf{h}_l \mathbf{s}(n-l) + v(n), \quad (3)$$

where $\mathbf{s}(n) = [s_1(n), s_2(n), \cdots, s_{N_T}(n)]^T$, $v(n)$ is the additive white Gaussian noise (AWGN), $\mathcal{L}$ represents the channel tap. The detection of the data transmitted in the SS domain is performed over the observation window of L OFDM symbols. For ease of illustration and without loss of generality, we focus on the case of $N_T = 2$ in this paper. Furthermore, for ease of reference, we call the low-complexity method in [9] the "original method" in the sequel.

3. THE PROPOSED DETECTION METHOD

The original method performs the identification process by finding the minimized relative energy distance between the estimated and the ideal cyclic autocorrelation function (CAF) values [9]:

$$\hat{\Delta}_2 = \arg \min_{i \in [1,2,\cdots,N/2]} \frac{\left| \left| \hat{c}_r^{(L)}(b,i) \right| - \left| \tilde{c}_{r,\Delta_2=i}(b,i) \right| \right|}{\left| \tilde{c}_{r,\Delta_2=i}(b,i) \right|}. \quad (4)$$

where $\tilde{c}_{r,\Delta_2=i}(b,i)$ is the ideal CAF value under the condition that $\Delta_2 = i$, $\hat{c}_r^{(L)}(b,\tau)$ is the estimated CAF value obtained by collecting OFDM symbols within observation length of L. In this paper, we adopt an approximate identification process, which can be expressed as

$$\hat{\Delta}_2 = \arg \max_{j \in [1,2,\cdots,N/2]} \left| \hat{c}_r^{(L)}(b,j) \right|. \quad (5)$$

Through our extensive numerical investigations, we found that the judgement represented by (5) has virtually the same performance as (4). This is due to the fact that the $\tilde{c}_{r,\Delta_2=i}(b,i)$ has the same energy level for all the $i \in [1, 2, \cdots, N/2]$ in practice. Thus, the proposed identification method is much more concise, while maintaining the same performance.

The CAF estimation process can be written as

$$\begin{aligned} \hat{c}_r^{(L)}(b,\tau) &= \frac{1}{LM} \sum_{n=0}^{LM-1} r(n) r^*(n+\tau) W_M^{bn} \\ &= \frac{1}{LM} \sum_{n=0}^{LM-1} \left[\sum_{l=0}^{\mathcal{L}-1} \mathbf{h}_l \mathbf{s}(n-l) + v(n) \right] \cdot \\ &\quad \left[\sum_{l=0}^{\mathcal{L}-1} \mathbf{h}_l \mathbf{s}(n+\tau-l) + v(n+\tau) \right]^* W_M^{bn} \\ &= \frac{1}{LM} \sum_{n=0}^{LM-1} \cdot \\ &\quad \left[\sum_{l=0}^{\mathcal{L}-1} \mathbf{h}_l \sum_{q=\tau+l-\mathcal{L}+1}^{\tau+l} \mathbf{C}_s(n-l,q) \mathbf{h}_{\tau+l-q}^H + v(n) v^*(n+\tau) \right] W_M^{bn}, \end{aligned} \quad (6)$$

where $(\cdot)^H$ denotes conjugated transposition, $b \in [1, 2, \cdots, M]$ is the cyclic frequency, $\tau \in [1, 2, \cdots, M]$ denotes the lag parameter, $\mathbf{C}_\mathbf{s}(n,\tau)$ is the coherency of data symbols and

$$\mathbf{C}_\mathbf{s}(n,\tau) = \frac{1}{N_T N} \sum_{m=-\infty}^{+\infty} p(n-mM) p(n+\tau-mM) \mathbf{W}_\tau, \quad (7)$$

where

$$\mathbf{W}_\tau = \sum_{k=0}^{N-1} W_N^{k\tau} \begin{bmatrix} 1 & W_N^{-k\Delta_2} \\ W_N^{k\Delta_2} & 1 \end{bmatrix}. \quad (8)$$

3.1. Limitation of the original method

The bit-error-rate (BER) of the original method under scenario A and scenario B is investigated, where it is assumed that

Table 1. Simulation parameters

Parameters	Values
FFT Size	128
CP Length	32
Channel Coding	Convolutional Code (5,7)
Coding Rate	1/2
Antenna Configuration	2×1
Modulation	QPSK

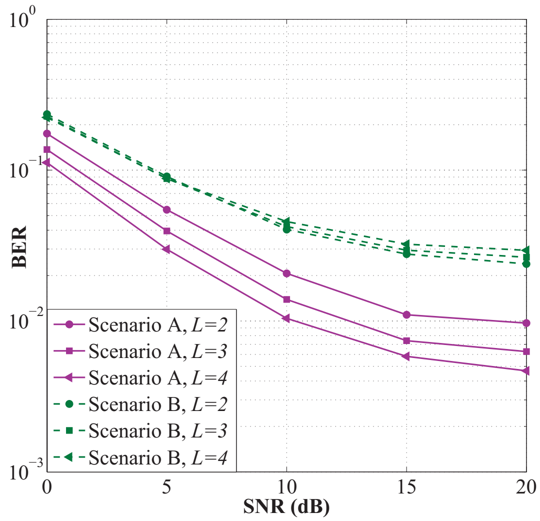

Fig. 2. Performance of the original method. Scenario A: channel coefficients are static within observation window length; Scenario B: channel coefficients are dynamic within observation window length.

under flat fading conditions, and the channel coefficients are complex Gaussian with zero means and unit variances. Other major simulation parameters are listed in TABLE 1. The corresponding simulation result is depicted in Fig. 2.

From Fig. 2, we can observe that the original method does not acclimate the channel conditions well in scenario B. The performance has an evident disparity in scenario B than in scenario A, under the same observation window lengths and SNR conditions. Analytically the deficiency shown in the simulation is understandable. According to (6), in scenario B, the symbol coherency $\mathbf{C_s}(n,\tau)$ in the estimated CAF value $\hat{c}_r^{(L)}(b,\tau)$ is distorted by the cumulative product effect of dynamic random channel coefficients $\mathbf{h}_l$ within observation window, which deteriorates the detection performance; while for scenario A, the coherency remains as the channel coefficients are static within observation window. Based on such observation, we propose an adaptive detection method in the next section, which is shown to be highly effective in mitigating this performance degradation.

3.2. A simplified case to clarify the suitability of proposed method

For ease of explanation, we first focus on scenario B and propose a simplified version of the proposed detection method as follows. The estimation process can be expressed as

$$\begin{aligned}\hat{c}_r^{(L)}(b,\tau) &= \frac{1}{L}\sum_{i=0}^{L-1}\left|\frac{1}{M}\sum_{n=iM}^{(i+1)M-1} r(n)r^*(n+\tau)W_M^{bn}\right| \\ &= \frac{1}{L}\sum_{i=0}^{L-1}\left|\frac{1}{M}\sum_{n=iM}^{(i+1)M-1}\cdot\right. \\ &\left.\left[\sum_{l=0}^{\mathcal{L}-1}\mathbf{h}_l\sum_{q=\tau+l-\mathcal{L}+1}^{\tau+l}\mathbf{C}_s(n-l,q)\mathbf{h}^H_{\tau+l-q}+v(n)v^*(n+\tau)\right]W_M^{bn}\right|.\end{aligned} \tag{9}$$

The identification process is then implemented by finding the maximized estimated value $\hat{c}_r^{(L)}(b,\tau)$ and returning the corresponding cyclic delay, i.e.,

$$\hat{\Delta}_2 = \arg\max_{j\in[1,2,\cdots,N/2]}\hat{c}_r^{(L)}(b,j)\,. \tag{10}$$

We can see that in scenario B, compared to the original method, the proposed method can preserve the coherency of estimated values from the "whitening effect" of the dynamical channel by isolating the varying channel coefficients with the norm operator. Specifically, from (6) we can see that the symbol coherency $\mathbf{C_s}(n,\tau)$, which is the key element to determine the detection process, has a cumulative product effect with the channel coefficients $\mathbf{h}_l$. Thus, under scenario B, the estimated CAF values of original method suffer a whitening effect from the dynamic complex channel coefficients, which severely hinders its performance. On the contrary, the proposed method can significantly surpasses this negative effect. Referring to (9), the proposed estimator calculates the norms of CAF values for each OFDM symbol length before accumulation. Under this condition, the cumulative products between symbol coherency $\mathbf{C_s}(n,\tau)$ and the dynamic channel coefficients $\mathbf{h}_l$ are preserved in norms with each OFDM symbol length. The performance boost is clearly demonstrated in our simulation result, which is depicted in Fig. 3.

Furthermore, from the figure, for the proposed method, we can see clearly a viable performance increase for every increased observation window length L. This demonstrates that the proposed method can effectively achieve the so-called diversity gain of the fading channel (via time diversity in this case). To further elaborate this, under scenario B, for the original method, if one OFDM symbol is in deep fading, the detection performance will be severely affected since it might cause a large negative effect to the CAF; while for the proposed method, the deep fading event is contained by the norm operation and only affect one term among L terms.

However, this simplified version of the proposed method is not universally better than the original method in all cas-

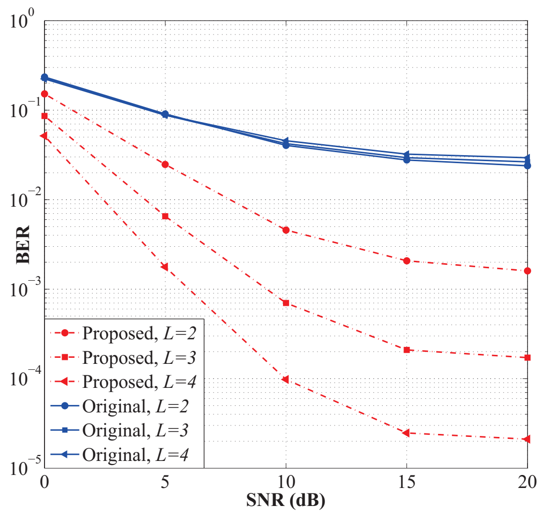

Fig. 3. Performance comparison under coefficient-dynamic observation window (scenario B).

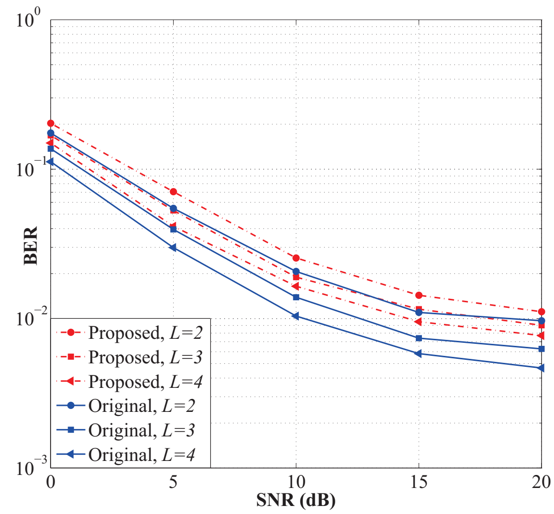

Fig. 4. Performance comparison under coefficient-static observation window (scenario A).

es. In Fig. 4 the performance of the two methods under scenario A is shown, where the channel coefficients are kept static within the observation window. The original method performs better in this case. Still referring to equation (9), when the proposed estimator preserves the symbol coherency by calculating the norms of CAF values for each OFDM symbol length before accumulation, it also preserve the coherency of noise from whitening effect. Thus, under coefficient-static observation window conditions, the performance of this simplified version is slightly impeded, compared with the original method.

3.3. The general case

In this subsection, we propose a generalized version of the method proposed in (9) and (10). For generality, we define scenario C as an intermediate scenario between the two extreme scenarios: the scenario A and B. In scenario C, the channel coefficient is static over K consecutive OFDM symbols, where K is a positive integer and $K \leq L$.

Verbally, the proposed method can be defined for scenario C as first collecting L OFDM symbols within the observation window, and then calculating the CAF values for each K OFDM symbols that share the same channel coefficients. Subsequently it sums up the norms of all the CAF values and normalizes the sum with observation window length L. And finally it performs detection via picking up the maximum estimator. Each part of CAF over K consecutive OFDM symbols, before the norm operation, is defined as:

$$\hat{c}_r^{(K)}(b,\tau) = \frac{1}{KM}\sum_{n=0}^{KM-1} r(n)r^*(n+\tau)W_M^{bn}. \tag{11}$$

The generalized version is an adaptive method. We can see that in scenario A, the proposed method is the same as the original method in [9]; while in scenario B, it is identical with the simplified method as (9) and (10). Thus, this method can adapt to the varying rate of the channel. In scenario C, it can be expected that the proposed method will work well under different channel varying rates and this is demonstrated by our simulations as well. It is noteworthy that the scenarios considered in this paper are theoretically ideal cases. Scenario C is a general case of scenario A and scenario B, which models fading channel with different varying rates. However, since K is an integer, it does not model the case that the varying rate of the channel is not an integer multiple of the OFDM symbol length. In practice, for such cases, one can still use the proposed method and perform truncating when deciding which OFDM symbols are grouped together for the norm operation.

Due to space limit, further details for simulation results of scenario C are omitted in this paper. We are preparing a journal paper which will contain all these details above.

4. CONCLUSION

In this paper, we propose an adaptive low-complexity detection method for signal transmission in the statistical spectrum domain, under time-varying channels. Numerical results show that the performance of the proposed method significantly surpasses the original method under coefficient-dynamic observation window, while maintaining low complexity.

5. REFERENCES

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