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Blind Estimation of Channel Order and SNR for OFDM Systems

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ABSTRACT In this paper, blind channel order and signal to noise ratio (SNR) estimators based on time-varying autocorrelation function (TVAF) are proposed for orthogonal frequency division multiplexing systems. The TVAF of the received signal reveals clearly the inherent periodicity introduced by cyclic prefix (CP) and carries rich information of channel and additive noise. To investigate the relationships among the TVAF, channel order, and SNR, a newly close-form expression of the TVAF of the received signal is derived. Not only the CP-induced TVAF components but the channel-spread TVAF elements are employed to derive the proposed estimators. Specifically, the two kinds of the TVAF components are separate from the components superimposed by the additive noise, which enables optimal estimation performance even for the low SNR regime. Numerical results show that, in contrast with the alternative methods, the proposed estimators achieve significant performance gain in the low SNR regime, while hold competitive performance in the high SNR regime.

INDEX TERMS OFDM, channel order estimation, SNR estimation, time-varying autocorrelation function.

I. INTRODUCTION

Orthogonal Frequency Division Multiplexing (OFDM) technology [1] has been widely used in almost all wireless communication systems due to its robustness to multipath propagation and efficiency for high-data-rate transmission. In an OFDM system, a cyclic prefix (CP) is appended in front of each OFDM symbol to resist inter-symbol interference (ISI). For many channel estimation and equalization algorithms, channel order is required to be estimated accurately in advance, e.g., for the channel correlation matrix in minimum mean square error (MMSE) channel estimation [2] and the length of blind equalizer [3], otherwise significant performance loss will be observed [4]. In addition, the channel order is usually estimated before the CP-based noise variance estimation, for the sake of using the CP samples without ISI. On the other hand, noise variance or signal to noise ratio (SNR) is an important parameter to evaluate channel quality, which can be applied in many algorithms such as adaptive modulation and coding, cognitive radio, and feedback-assisted radio resource management, etc. Hence, accurate estimation of channel order and SNR is of prime importance to improve the performance of many communication applications.

There are some available methods for channel order estimation in the literature. Based on information theoretic criteria, three typical methods, i.e., the minimum description length (MDL) [5], the Akaike information criteria (AIC) [6], and the Liavas algorithm [7], are investigated for the channel order estimation, which are sensitive to the SNR variations. Tong and Zhao [8] present a deterministic algorithm for order detection and channel estimation, which offers perfect channel order estimation under the noise-free case. The method in [9] is based on the minimization of the mean square error with the knowledge of channel window. A cost function built with the information of channel matrices is designed to find the effective channel order in single-input multi-output (SIMO) systems [10]. In [11], a channel order estimation algorithm is developed by comparing the autocorrelation values of the received signal with a derived threshold, where the critical threshold depends on the sample size, the SNR, and the leading/last channel coefficients. The high order cumulant features are exploited in [12] to improve the performance of the channel length estimation at low SNRs.

Without the knowledge of pilot symbols or training sequence, blind SNR estimators are well motivated for in-service estimation, high bandwidth efficiency applications, and sensing for cognitive radio or communication electronic warfare. Numerous blind noise variance or SNR estimators have been investigated over recent decades. The work in [13] exploits the spectrum in the guard band for noise variance estimation, where the estimation performance is easily affected by spectrum leakage. In [14], a noise variance estimator is proposed based on expectation maximization (EM) algorithm under the assumption that the channel is known. The traditional moment-based algorithm, M2M4 algorithm [15], uses the second and fourth order autocorrelation of the received signals and performs quite well with constant modulus (CM) constellations. Based on a linear combination of the ratios of certain high even-order moments, the SNR estimator in [16] shows well performance for multilevel constellations at intermediate and high SNRs. In addition, a number of blind SNR estimators based on the CP-induced correlation, without requiring the information of channel and signal constellation, have been studied widely in [17]–[20].

For the SNR estimators based on the CP-induced redundancy, the channel order is often used as an input in the estimation algorithms so as to make use of the CP samples without ISI, and thus it would be estimated before the SNR estimation. By using the CP-introduced correlation structure, the method in [17] creatively proposes a joint estimator of power delay profile and noise variance based on maximum likelihood (ML) algorithm, where the noise variance estimation method has been widely adopted in the following studies of SNR estimation. However, the performance of the maximum delay time estimation is sensitive to a subjective choice of threshold, resulting in the performance loss of noise variance estimation at low and high SNRs. To address these issues, Socheleau and Houcke [18] exploit the correlation and the cyclic autocorrelation induced by the CP for channel order and SNR estimation, where the channel length is estimated through maximizing the geometric mean of individual likelihood elements. Threshold is not required in this method anymore and the estimation performance is improved to some extent. In [19], a new SNR estimation method by using the CP-induced redundancy is presented, where the channel order estimation is solved by the MDL or the AIC algorithm. This method based on the information theoretic criteria provides significant performance gain in the high SNR region, but with a cost of performance deterioration in the low SNR region. On the basis of the CP-induced correlation and the cyclic structure of OFDM symbols, the work in [20] develops a signal power estimator without the knowledge of the channel length. It can be found that the basis of all the aforementioned CP-based SNR estimation methods is to exploit the difference between the CP and its repetition part of the data symbol.

It is noted that a common problem of the existing blind methods for channel order and SNR estimation is the performance degradation at low SNR values. Some of the improved methods count on high-order statistics to address this issue at the cost of high computational complexity. Due to the robustness to noise and interference, the cyclostationarity of signal has been widely applied in parameter estimation [21], [22]. Motivated by these facts, the cyclostationarity of the received signal characterized by second-order statistics is exploited in this paper. The second-order statistics of a cyclostationary signal can be described by time-varying autocorrelation function (TVAF), cyclic autocorrelation function (CAF), and spectral correlation density (SCD) function [23]. The TVAF, with the simplest expression, is the basis for the derivation of the CAF and the SCF. Based on the CAF or SCD, the signal cyclostationarity has been employed to estimate channel order and SNR [24]–[26]. At the receiver, the TVAF reveals clearly the inherent periodicity of the transmitted signal and carries rich information of channel and additive noise, which can also be employed for channel order and SNR estimation. To the best of our knowledge, there is little literature available that exploits the TVAF for channel order and SNR estimation.

In this paper, a blind method of channel order and SNR estimation based on the TVAF of the received signal is proposed for OFDM systems over unknown frequency selective fading channels. Since CP produces the copies of the last part of each OFDM symbol periodically, an OFDM signal with CP exhibits the second order cyclostationarity [27], [28]. Unlike the above estimation methods, we investigate directly the correlation characteristics of the received OFDM signal from the TVAF viewpoint. A newly close-form expression of the TVAF of the received signal is derived, where the complicated effect of multiple paths is relaxed. Based on this, the relationships among TVAF components, noise variance, channel order, and channel power are theoretically established. The CP-induced and the channel-spread TVAF components carry rich channel information and are separate from the components superimposed by the additive noise, which can be exploited to improve the performance of channel order and SNR estimation.

The rest of this paper is organized as follows. Section II describes the system model. Section III details the TVAF of the received signal over frequency selective fading channels. In Section IV, a blind method for channel order and SNR estimation is proposed based on the TVAF of the received OFDM signal. Then simulation results are discussed in Section V. Finally, conclusions are given in Section VI.

II. PROBLEM FORMULATION

Consider a discrete-time OFDM system with N sinusoidal subcarriers, each of which is applied with quadrature amplitude modulation (QAM) to map the binary digits to complex data streams. The parallel complex data streams are modulated by an inverse fast Fourier transform (IFFT). In order to eliminate ISI caused by multi-path fading channel, a CP is added in front of every OFDM symbol which is a copy of the last part of the IFFT output. Consequently, the discrete-time baseband equivalent transmitted signal can be given by

$$s(n) = \frac{1}{\sqrt{N}} \sum_{m=-\infty}^{+\infty} \sum_{k=0}^{N-1} d_{m,k}\, g(n - mM)\, e^{\frac{j2\pi k(n-mM)}{N}}, \quad (1)$$

where $d_{m,k}$ represents the transmitted complex data symbol at the kth subcarrier of the mth OFDM symbol. We assume that the data symbols are statistically independent from each other such that $E\left\{d_{m,k} d^*_{m',k'}\right\} = \delta(m - m')\delta(k - k')$, where $E(\cdot)$, $\delta(\cdot)$, and superscript $(\cdot)^*$ denote the mathematical expectation, the Delta function, and the complex conjugation, respectively. $g(n)$ refers to an M-length rectangular window. M is the length of an OFDM symbol with CP, i.e. $M = N + N_g$, where N_g is the length of CP.

The OFDM signal is then transmitted serially through an unknown frequency selective fading channel with AWGN. Assuming that the synchronization is perfect at the receiver, the discrete-time received signal with K OFDM symbols can be expressed as

$$r(n) = \sum_{l=0}^{L-1} h(l)s(n - l) + v(n), \;\; 0 \le n \le KM - 1, \quad (2)$$

where $h(l)$ denotes the channel impulse response of the lth channel tap and L is the channel order. In order to eliminate ISI, N_g is set to be larger than L. The noise component $v(n)$ is a zero-mean white noise with variance σ_v^2.

The SNR at the receiver is defined as

$$SNR = \frac{S}{\sigma_v^2}, \quad (3)$$

where $S = \sum_{l=0}^{L-1} |h(l)|^2$ is the signal power of channel output.

III. TIME-VARYING AUTOCORRELATION FUNCTION OVER FREQUENCY-SELECTIVE CHANNELS

Normally, the cyclostationarity of a random process can be characterized in terms of the time-varying autocorrelation function, which is a 2-D function with respect to time index and lag parameter. In an OFDM system, the CP insertion operation produces the periodical copies. This makes the autocorrelation function of a CP-OFDM signal time-dependent and periodic in time.

The TVAF of a zero mean complex cyclostationary signal $s(n)$ is defined as

$$c_s(n, \tau) = E\left\{s(n)s^*(n + \tau)\right\}, \quad (4)$$

where τ is an integer lag parameter. By substituting (1) into (4), the TVAF of the OFDM transmitted signal can be obtained as

$$c_s(n, \tau) = \Upsilon_N(\tau) \sum_{m=-\infty}^{\infty} g(n - mM)g(n + \tau - mM), \quad (5)$$

where $\Upsilon_N(\tau) = \frac{1}{N}\sum_{k=0}^{N-1} e^{-j2\pi k\tau/N}$. It can be verified that $c_s(n, \tau)$ is M-periodic in n for each value of τ, i.e., $c_s(n, \tau) = c_s(n + M, \tau)$.

Using (2) and (4), the TVAF of the received OFDM signal $r(n)$ can be given as [27]

$$c_r(n, \tau) = \sum_{l=0}^{L-1} \sum_{\xi=\tau+l-L+1}^{\tau+l} h(l)h^*(l + \tau - \xi)c_s(n - l, \xi) + c_v(\tau), \quad (6)$$

where $c_v(\tau) = \sigma_v^2\delta(\tau)$ and $\xi = \tau + l - l'$ $(0 \le l \le L - 1$ and $0 \le l' \le L - 1)$. Since $c_s(n, \tau) = c_s(n + M, \tau)$, we can obtain $c_r(n, \tau) = c_r(n + M, \tau)$ for every τ, which shows that $r(n)$ is also a cyclostationary random process with cyclostationary period M.

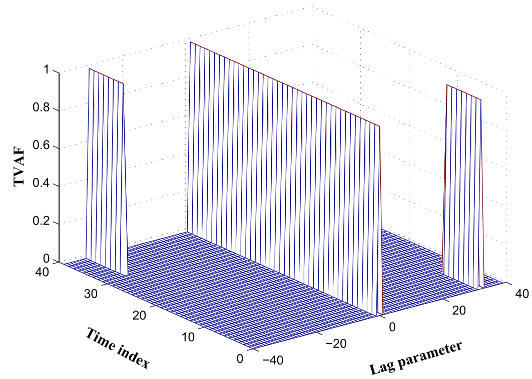


FIGURE 1. TVAF of the transmitted OFDM signal.

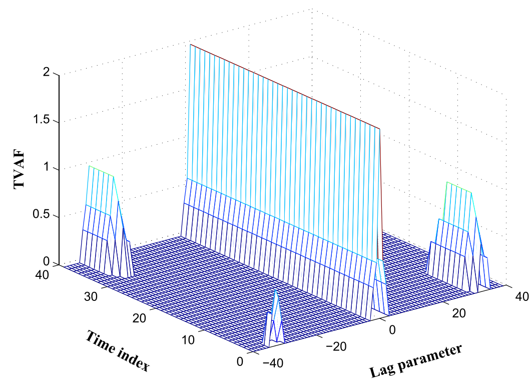


FIGURE 2. TVAF of the received OFDM signal over frequency-selective channels.

Fig. 1 illustrates the TVAF of the transmitted OFDM signal within one period, where $N = 32$ and $N_g = 8$. It can be seen that all the nonzero autocorrelation peaks have the value of 1 and appear at the three cross sections with $(\tau = 0, \pm N)$. The components at $\tau = \pm N$ characterize the correlations introduced by the CP, where the time varying characteristic is in a ladder manner. The peaks at $\tau = 0$ interpret the correlations induced by signal itself which are invariant in time n. Fig. 2 describes the TVAF of the received OFDM signal over a frequency-selective fading channel for SNR of 0 dB, where L is set to be 3. It shows that the autocorrelation function of the received signal is spread with respect to the lag parameter dimension due to the multipath delay effect. The channel-spread TVAF components still have comparatively obvious peaks, which inspire an interesting means to estimate channel order. In addition, since the values of $c_v(\tau)$ are zero unless $\tau = 0$, the stationary noise only distorts the information on $c_r(n, 0)$.

IV. PROPOSED CHANNEL ORDER AND SNR ESTIMATORS BASED ON TVAF

The TVAF of the received signal provides a comprehensive view on the CP-induced redundancy and the channel effect at the receiver. It can be found that the channel-spread and the CP-induced TVAF components carry rich channel information and are free of additive noise, which can be exploited for channel order and SNR estimation. In this section, based on the TVAF of the received signal, the channel order is first estimated and the SNR estimation can be performed subsequently by combined use of the estimated channel order.

A. CHANNEL ORDER ESTIMATION

It can be seen that the expression of $\Upsilon_N(\xi)$ in (5) determines that the nonzero values of $c_s(n-l, \xi)$ occur when $\xi = 0, \pm N$. Since $\tau = \xi + l' - l$ and $-L+1 \leq l'-l \leq L-1$, the theoretical TVAF components of the received signal have nonzero values when $\xi - L + 1 \leq \tau \leq \xi + L - 1$ and $\xi = 0, \pm N$. Therefore the effect of multipath channel spreads each TVAF peak of the transmitted signal into two directions along the lag parameter axis, where the expansion number of the spread TVAF peaks in one direction relates to the channel order.

Theoretically, only the transmitter-induced TVAF components and their channel-spread TVAF elements have non-zero values. However, in practice, the TVAF of the received signal is obtained from the instantaneous estimate of $\hat{c}_r(n, \tau) = r(n)r^*(n + \tau)$ using a limited length of OFDM symbols, and therefore almost nonzero even if it equals zero theoretically at a certain (n, τ). Thus, the sample average of $c_r(n, \tau)$ is employed here to alleviate the effect of the estimation error of $c_r(n, \tau)$, which is given by

$$\tilde{c}_r(\tau) = \frac{1}{KM} \sum_{n=0}^{KM-1} c_r(n, \tau). \tag{7}$$

Based on the above analysis, it is certain that the theoretical TVAF values of the received signal are zero when $N_g \leq \tau \leq N - N_g$. This provides the reference for the threshold design of the channel order estimator. The channel order is determined by comparing the sample average of $c_r(n, \tau)$ with a threshold, where the latter is also computed from the former. The threshold of the proposed channel order estimator can be written as

$$\Gamma = \max\left\{|\tilde{c}_r(\tau_0)|\,, \tau_0 \in \Omega\right\}, \tag{8}$$

where $\Omega = \left\{N_g, \cdots, N - N_g\right\}$. The notations of $\max\{.\}$ and $|\,.\,|$ denote the maximum operation and the modular arithmetic respectively. In order to reduce the influence of noise uncertainty on estimation performance, we introduce a counter in the algorithm such that the judgment process won't be terminated until the judgment results are false for Q consecutive trials. The minimum value of Q is 1. Finally, the proposed algorithm for the channel order estimation can be summarized as follows:

Step 1) Compute $\tilde{c}_r(\tau)$ and Γ according to (7) and (8) separately. Initialize $q = Q$ and $L_0 = 1$.

Step 2) Compare $|\tilde{c}_r(L_0-1)|$ with the threshold Γ. If $|\tilde{c}_r(L_0-1)|$, determine $\hat{L} = L_0$. Then reset $q = Q$ and go to step 4. Otherwise, go to step 3.

Step 3) Decrease q by 1. Go to step 4 until q=0.

Step 4) Increase L_0 by 1. Go to step 2 until $L_0 = N_g$.

B. SNR ESTIMATION

By substitution of (5) into $c_s(n - l, \xi)$ in (6), we can obtain

$$c_s(n-l, \xi) = \begin{cases} 1 & \textit{for } N \leq ((n-l) \bmod M) \leq M-1 \textit{ and } \xi = -N \\ 1 & \textit{for } 0 \leq ((n-l) \bmod M) \leq N_g - 1 \textit{ and } \xi = N \\ 1 & \textit{for } \xi = 0 \\ 0 & \textit{otherwise}, \end{cases} \tag{9}$$

where mod stands for the modulus operator. To decouple the effect of l of $c_s(n - l, \xi)$ in (6), the restricted support region of n is considered, in which the non-zero values of $c_s(n-l, \xi)$ equal 1 for different l at a given ξ. It can be found that this decouple operation also makes the used correlation components in the proposed estimator are not interfered by ISI. Consequently, the TVAF of the received signal can be derived as

$$c_r(n, \tau) = \sum_{l=0}^{L-1} \sum_{\xi=\tau+l-L+1}^{\tau+l} h(l)h^*(l + \tau - \xi)f(n, \xi) + c_v(\tau), \tag{10}$$

where

$$f(n, \xi) = \begin{cases} 1 & \textit{for } N + L - 1 \leq (n \bmod M) \leq M - 1 \\ & \quad \textit{and } \xi = -N \\ 1 & \textit{for } L - 1 \leq (n \bmod M) \leq M - N - 1 \\ & \quad \textit{and } \xi = N \\ 1 & \textit{for } \xi = 0 \\ 0 & \textit{otherwise}. \end{cases} \tag{11}$$

Letting $\tau = \xi$, (10) can be further simplified as

$$c_r(n, \tau) = f(n, \tau) \sum_{l=0}^{L-1} |h(l)|^2 + c_v(\tau). \tag{12}$$

Furthermore, we can obtain $c_r(n, \tau)$ for $\tau = 0, \pm N$ as

$$c_r(n, \tau) = \begin{cases} \sum_{l=0}^{L-1} |h(l)|^2 + \sigma_v^2 & \tau = 0 \\ f(n, \tau) \sum_{l=0}^{L-1} |h(l)|^2 & \tau = \pm N. \end{cases} \tag{13}$$

Based on the CP-induced nonzero TVAF components, the noise variance can be estimated as

$$\hat{\sigma}_v^2 = \frac{1}{2KP}\left\{\sum_{i=1}^{K}\sum_{j=1}^{P}\left[c_r(n_{1_{i,j}},0) - c_r(n_{1_{i,j}},-N) + c_r(n_{2_{i,j}},0) - c_r(n_{2_{i,j}},N)\right]\right\}, \quad (14)$$

where

$$\begin{aligned} P &= N_g - L + 1 \\ n_{1_{i,j}} &= (i-1)M + N + L + j - 2 \\ n_{2_{i,j}} &= (i-1)M + L + j - 2. \end{aligned} \quad (15)$$

As can be seen from (11) and (13), the elements of $c_r(n,\tau)$ with $\tau = 0, \pm N$ carry the information of the signal power of channel output. Here, the components of $c_r(n,0)$ are employed to estimate signal power, since they hold more effective information than those of $c_r(n,-N)$ and $c_r(n,N)$. Accordingly, the signal power of channel output can be obtained by

$$\hat{S} = \frac{1}{KM} Re\left\{\sum_{n=0}^{KM-1}\left[c_r(n,0) - \hat{\sigma}_v^2\right]\right\} \quad (16)$$

where $Re\{x\}$ denotes the real part of x. To improve the SNR estimation performance degraded by the channel order underestimation, we can use $L=\hat{L}+C$ in (15) for the SNR estimation, where C is chosen as a nonnegative integer. Based on (3), (14) and (16), the SNR estimation can then be calculated.

V. NUMERICAL RESULTS

In this section, computer simulations are carried out to evaluate the performance of the proposed estimators. The OFDM signal has 256 subcarriers and the length of the CP samples is 32. The OFDM symbol duration with CP is 28.8 μs. Subcarriers are modulated by QPSK. The multipath channel model adopted is the COST 207 Rural Area (RA) model with $L = 6$ [29]. Without the loss of generality, the channel gain is scaled such that $\sum_{l=0}^{L-1}|h(l)|^2 = 1$. Estimation is then carried out using Monte Carlo method with $N_I = 10000$ runs.

To evaluate the performance of the channel order estimator, the probability of correct detection (PoCD) [30] and the frequency of occurrence (FoO) [31] are used, which can be defined as

$$PoCD = \frac{\eta_{\hat{L}=L}}{N_I}, \quad (17)$$

and

$$FoO(l) = \frac{\eta_{\hat{L}=l+1}\cdot 100}{N_I}, \quad (18)$$

where $\eta_{\hat{L}=L}$ and $\eta_{\hat{L}=l+1}$ denote the cumulative total of the number of times for $\hat{L} = L$ and $\hat{L} = l+1$ respectively. Furthermore, the alternative algorithms in [18] and [19] are involved for comparing the performance of the channel order estimation, where the MDL criterion is used for the method in [19]. Additionally, the SNR estimation performance is evaluated in terms of the normalized mean-square error (NMSE) as shown in [32], which is given by

$$NMSE = \frac{1}{N_I}\sum_{i=1}^{N_I}\left(\frac{\hat{\rho}_i - \rho}{\rho}\right)^2, \quad (19)$$

where $\hat{\rho}_i$ is an estimate of the noise variance, or the signal power, or the SNR for the ith trial. ρ is the true value of ρ_i. Noting that the SNR values used in (19) are the real values (i.e., not dB's). To compare the SNR estimation performance with the proposed method, the methods in [18]–[20] are considered in the simulations, where β is set to be 5 for the method in [18]. It is worthwhile to note that all the considered existing methods use the noise variance estimation algorithm proposed in [17] to estimate noise variance. Since the channel order estimation is not involved in the method in [20], the noise variance is estimated using the true channel order.

Fig. 3 depicts the probability of correct detection of the channel order versus SNR for $K = 100$. The optional parameter Q with the values of 1, 2, and 4 is investigated for the proposed channel order estimator. It can be seen that the proposed estimator, with any Q of interest, outperforms the estimator in [18] by a substantial margin. It is also superior to the estimator in [19] in the low and mediate SNR regime, while slightly inferior to that one in the high SNR regime. The reason for this inferior performance at high SNR is that, in contrast with the method in [19], the proposed algorithm engenders a little more underestimated channel orders caused by instantaneous estimation error. On the other hand, the proposed estimator has an improved detection performance as Q increases from 1 to 2. When Q is further increased, the PoCD results of the proposed estimator for the cases of Q= 2 and Q= 4 are close over a wide range of SNR. On the whole, the proposed estimator provides an optimal estimation in finding the true channel order even at low SNR values, and the advantages over the other existing estimators are almost maintained for different Q.

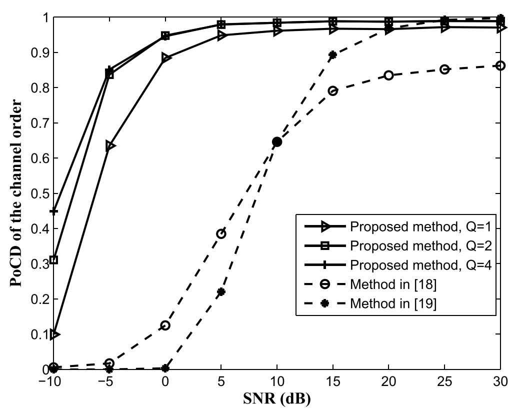
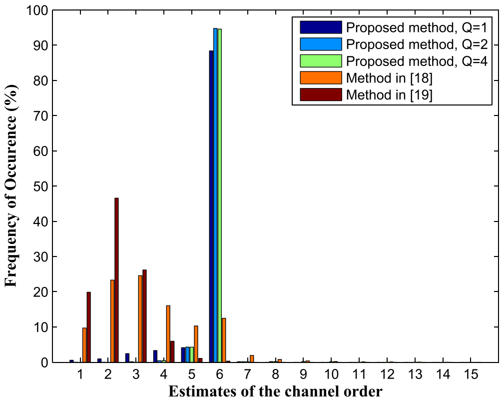
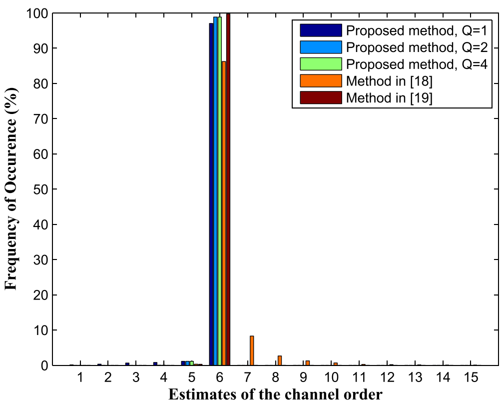


FIGURE 3. PoCD of the channel order versus SNR for $K = 100$.

The frequency of occurrence of the estimated channel order for $K = 100$ is demonstrated in Fig. 4. Fig. 4(a) and



(a)



(b)

FIGURE 4. Frequency of occurrence of the estimated channel order for $K = 100$.

Fig. 4(b) illustrate the FoO performance for SNRs of 0 dB and 30 dB separately. It can be seen that the FoO results of the true channel order in Fig. 4 comply with the PoCD results in Fig. 3. From Fig. 4(a), we can observe that all the considered estimators deliver low channel order estimates. The method in [19] has the most severe underestimation, followed by the method in [18]. The class of the proposed estimators has the fewest underestimated results, most of which are close to the actual channel order. On the other hand, the overestimation phenomenon for all the methods is relatively slight, where it happens most frequently for the method in [18]. Fig. 4(b) shows that the estimation accuracies of the methods in [18] and [19] have been enhanced considerably for SNR of 30 dB. The underestimation and overestimation for all the considered methods are weak, where the proposed estimator and the method in [18] have relatively obvious underestimation and overestimation respectively.

Fig. 5 presents a comparison for the PoCD performance of the channel order versus the number of symbols for SNR of 10 dB. For all the considered methods, more accurate channel order estimates can be obtained by increasing the amount of the symbols used for estimation. The PoCD curves of the proposed method with $Q= 2$ and $Q= 4$ overlap, where the PoCD values are higher than those of the proposed method

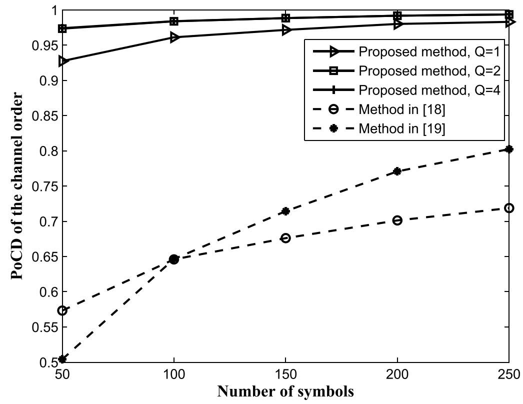


FIGURE 5. PoCD of the channel order versus number of symbols for SNR of 10 dB.

with $Q= 1$. Meanwhile, the group of the proposed estimators outperform the estimators in [18] and [19] significantly. In addition, the PoCD results of the method in [19] is first lower than and then surpass those of the method in [18] with the increase of the number of symbols. From Fig. 3 to Fig. 5, we can see that the proposed estimator with $Q= 2$ shows well performance for different number of symbols over the whole range of SNR values and is therefore chosen for the proposed method in the following comparisons.

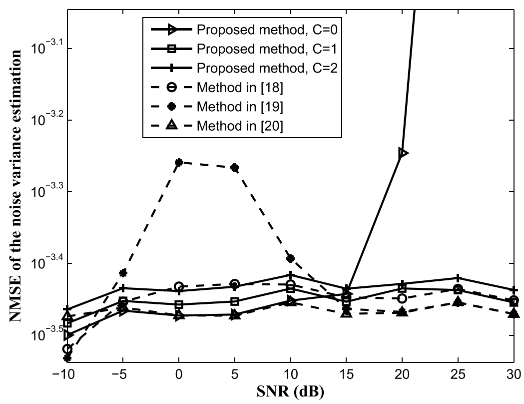


FIGURE 6. NMSE of the noise variance estimation versus SNR for $K = 100$.

In Fig. 6, the NMSE performance of the noise variance estimation as a function of SNR is illustrated. The optional parameter C of the proposed SNR estimator is set to be 0, 1 and 2, respectively. Among the considered estimators, the estimator in [20], which uses the true channel order for noise variance estimation, has the lowest NMSE results. It can be further observed that all the algorithms have approximately comparable NMSE performance, with the exception of the method in [19] in the relatively low SNR regime and the proposed method with $C= 0$ at high SNRs. Since the noise power is predominant at low SNRs, a moderate underestimation of channel order has little influence on the noise variance estimation performance. However, that is not true for an exorbitant underestimation at low SNRs and a slight underestimation at high SNRs. This is why the performance degradation happens for the two cases mentioned above. As the underestimation poses much more performance degradation than the overestimation [4], the underestimated results should be avoided as much as possible. A solution to the performance loss of the proposed estimator with $C= 0$ can be found by increasing C at least by 1, since the underestimated values in this case are mostly less than the actual channel order by 1. The NMSE results of the proposed method with $C= 1$ and $C= 2$ verify that. Noting that there is no need to further increase C after considering the tolerance of the underestimation of the channel order. Hence, in the following, we use $Q= 2$ and $C= 1$ for the proposed estimator for performance evaluation in comparison with the other existing estimators.

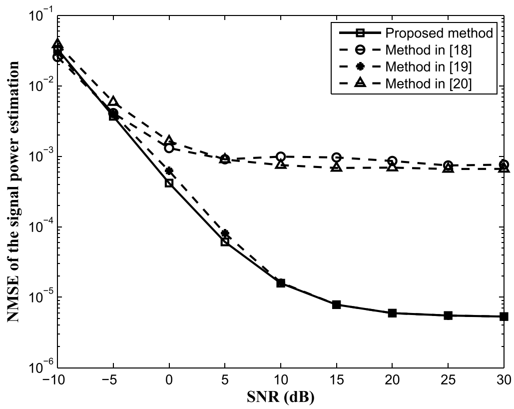


FIGURE 7. NMSE of the signal power estimation versus SNR for $K = 100$.

Fig. 7 plots the NMSE results of the signal power estimation versus SNR for $K = 100$. From Fig. 7, we can see that the proposed method almost outperforms all the other conventional methods, except that it has a slightly higher NMSE value than the method in [18] for SNR of -10 dB. The reason for the performance superiority of the method in [18] at $SNR = -10\,dB$ is that the lower cyclic autocorrelation components induced by the CP, which are distorted severely by the additive noise, are not adopted in the method in [18] for the signal power estimation. Thanks to the high detection performance of the proposed channel order estimator, our proposed method not only performs the best in the high SNR regime, but also improves the estimation performance in the low SNR regime.

Fig. 8 compares the SNR performance of the proposed method with the traditional methods for $K = 100$. The NMSE performance with perfect knowledge of the channel order and the signal power is plotted as a lower bound for CP-based blind SNR estimation [19]. As the theoretical benchmark, the data-aided (DA) normalized Cramér-Rao lower bound (NCRLB) is also plotted as a theoretical lower bound for SNR estimation [32]. Compared with the existing methods, the NMSE performance curve of the proposed method nearly coincides with the performance bound with perfect knowledge of L and S at high SNRs and is closer

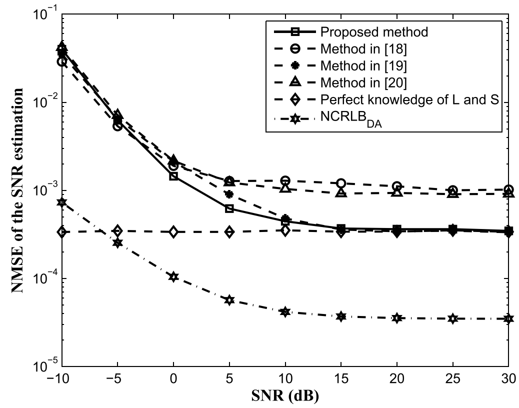


FIGURE 8. NMSE of the SNR estimation versus SNR for $K = 100$.

to that bound as well as the DA NCRLB for almost all the SNR values. As can be seen from Fig. 8, when SNR is larger than or equal to 10 dB, the proposed method performs as well as the method in [19], and shows obviously better performance than the methods in [18] and [20]. In the low SNR regime, the proposed method generally holds better performance than all the conventional methods. Overall, the proposed estimator exhibits the best SNR estimation performance for almost all the SNR values of interest.

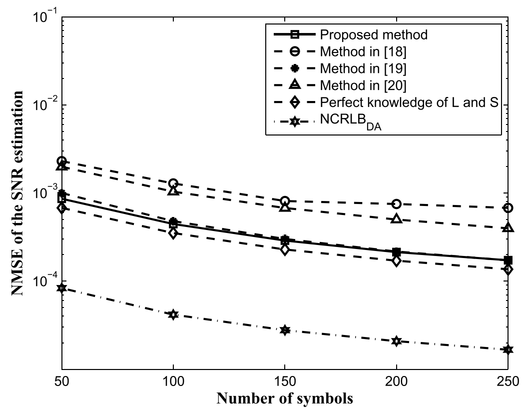


FIGURE 9. NMSE of the SNR estimation versus number of symbols for SNR of 10 dB.

Fig. 9 shows the NMSE performance of the SNR estimation as a function of the number of symbols for SNR of 10 dB. It is obvious that the NMSE results of all the considered estimators decrease as the number of symbols increases. The downward trend of the NMSE results of the considered SNR estimators is approximately the same except that the estimator in [18] has a slowing decline when the number of the used symbols is larger than 150. The performance loss of the method in [18] for large number of symbols is the fact that the abandoned cyclic autocorrelation components induced by the CP become beneficial for SNR estimation in the case of $K > 150$ and $SNR = 10\,dB$. Additionally, the proposed method is slightly superior to the method in [19] which outperforms the method in [20] evidently, while the method in [20] shows a better performance than the method in [18].

VI. CONCLUSIONS

In this paper, a new blind method for the channel order and the SNR estimation is proposed based on the TVAF of the received signal. The channel-spread TVAF components indicate the information of the channel order, which can be exploited for channel order estimation. The CP-induced TVAF elements carry rich channel information and are separate from the components contaminated by the additive noise. This motivates us to derive the proposed SNR estimator. The noise-free property of the CP-induced and the channel-spread TVAF components supplies a basis for achieving excellent performance of the proposed estimators. In addition, it is clear that the proposed blind estimators do not require the knowledge of the channel and are constellation-independent. Simulation results show that the proposed method provides a more effective way to estimate the channel order and the SNR value than the other existing blind estimators.

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