Collaborative Blind Equalization for Time-Varying OFDM Applications Enabled by Normalized Least Mean and Recursive Square Methodologies

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ABSTRACT In this work, a collaborative blind equalization method for the orthogonal frequency division multiplexing (OFDM) signals in time-varying channels is presented. Equalizers are eliminated the inter-symbol interference (ISI) in the received signals caused by channel distortions. The conventional adaptive equalization requires sending the training-sequences periodically to synthesize the channel model, which can only provide redundant information, and consequently decrease the channel utilization and complicate the system. To overcome this drawback, the blind equalization methods, which need not send the training-sequences periodically, is developed. However, the conventional blind equalization methods still suffer from various disadvantages. The normalized least mean square (NLMS) method is able to converge rapidly, whereas its equalization error is relatively large. The recursive least square (RLS) method has smaller steady-state error but low convergence rate, demanding massive training sequences. To further enhance the equalization performance of time-varying OFDM systems, which is typically with massive calculation, a collaborative blind equalization is proposed in this work, which is able to effectively combine the characteristics of the conventional NLMS and RLS methods together. The numerical simulations demonstrate the proposed LM-RS method can exhibit quite good performance. Particularly, as compared with the conventional NLMS and RLS methods, the proposed LM-RS method achieves smaller steady-state error and lower complexity, as well as similar convergence rate. All these results indicate that the proposed collaborative LM-RS blind equalization method is suitable for the OFDM transmission under the time-varying wireless application environments.

INDEX TERMS Blind equalization, normalized least mean square (NLMS), orthogonal frequency division modulation (OFDM), recursive least square (RLS), time-varying channel.
As shown in Fig. 1, in the typically wireless and mobile communication system, the channel model is significantly influenced by the physical locations and structures of the scatters, which will induce the multi-path effect typically [3]. As the target moves or the channel parameters vary within time, the key factor influencing the ISI effect in the receiver will change as well. Therefore, the coefficients in the equalizer should be changed accordingly to match the real-time characteristics of the wireless channel [4]. Moreover, in the high-speed wireless communication environment, length of the cyclic prefix in the orthogonal frequency division multiplexing (OFDM) might be smaller than the maximum delay of the multi-path channel. Then, the Doppler shift effect in wireless channel can induce inter-subcarrier interference (ICI) into the OFDM signal [5], [6]. Hence, the conventional frequency domain equalization cannot fulfill requirements on the bit error rate (BER) of the received signal completely. Although the conventional adaptive equalization can relieve the ISI to a certain extent, it needs to continuously send the pre-known training sequences and periodically train the equalizer as well. The channel utilization is thereby reduced, which is quite disadvantageous for the high-speed wireless data transmission with limited spectrum resources. Fortunately, the blind equalization algorithm does not require to train the parameters of the equalization filter periodically [5]. In this way, the channel utilization can be improved greatly. Furthermore, as it is well known, the carrier synchronization in communications with coherent modulation/demodulation is quite important, but difficult to be realized. Different from the conventional adaptive equalization methods, the blind equalization only relates to the amplitude of the received signal, which deduces the requirement for carrier synchronization, and consequently be more conducive to the practical implementation of the communication system.

Moreover, the derived forms of OFDM, such as the filtered OFDM, the generalized frequency division multiplexing (GFDM) [7], and the universal filtered OFDM (UF-OFDM), might act significant roles in future beyond fifth-generation (5G) and sixth-generation (6G) mobile communications. Although the unique structure of the OFDM symbol is able to eliminate the ISI to some extent, performing relatively low ISI, there is still considerable ISI and ICI in some specific wireless environments like with large group delay or deep fading effect. Therefore, to mitigate or even eliminate the ISI between adjacent OFDM symbols and the ICI of adjacent OFDM sub-carriers, it is essential to introduce the equalization processing into the receiver. On the other hand, since the channel state information (CSI) of the communication system with OFDM is generally unknown, the blind estimation and blind equalization are highly demanded [8].

To meet the requirements of effective transmission without ISI in the time-varying channel, blind equalization algorithms that do not demand training-sequences have received extensive attention and been widely used in various communication systems. In [9], the least mean square (LMS) blind equalization method was introduced into the underwater communication systems to enhance the performance of the OFDM signals. It has achieved a low complexity as benchmark for the blind equalizer, and has shown similar convergence rate as the minimum mean square error (MMSE) equalizer in the static channel environment. Since this method is based on the statistical properties of the known signals, instead of the training-sequences, it is not suitable for the time-varying channel applications. The LMS blind equalization algorithm typically depends on the ability of making good decisions initially. However, in the fast time-varying channel, the initial decision usually does not converge to an exact value, and the associated error will influence the subsequent equalization process.

In recent years, several blind equalization algorithms based on the neural networks, such as the feed-forward neural network and the higher-order spectra, have been developed [10], [11]. These neural-network-based algorithms are able to operate complex logic calculations within nonlinear relationships, thus can overcome the shortcomings of the linear blind equalizers. Unfortunately, these methods will involve massive calculation and are time-consuming. Moreover, they are highly influenced by the accuracy of theory description as well as the hardware integration. Therefore, based on the aforementioned disadvantages, more and more attention has been paid to the hybrid equalizer structure instead of the single linear equalizer or nonlinear equalizer. On the other hand, a semi-blind equalization method for OFDM symbols is proposed in [12]. This semi-blind method assumes that the OFDM system needs not send the cyclic prefixes, which will improve the channel utilization. The disadvantage is that the accuracy of reconstruction cannot be verified in real time. Meanwhile, number of the cycles is related to the carrier-to-noise ratio. Hence, as number of the cycles is large, the transmission efficiency will be greatly reduced. In [13], the Kalman filter equalization of OFDM systems with insufficient guard spacing is proposed to improve the spectrum efficiency without any prior knowledge of channel statistics. Simulations demonstrated the proposed method outperforms the conventional least square (LS) or LMS methods, with the transmission efficiency being ensured. Its drawback is that the accuracy of the Cox-Ingersoll-Ross (CIR) estimation by the preamble symbol is not high enough to adapt to the fast changes of the time-varying channel.

FIGURE 1. Multi-path effect in the wireless channel between transmitter and receiver.
In a word, based on the summary mentioned above, for the time-varying channel environment, these equalization methods require large number of iterations to converge, with large amount of redundant calculation. To overcome such disadvantages, a blind equalization method with simple structure for OFDM signals in time-varying channel is proposed in this work. In the proposed method, the structure and associated algorithm are simultaneously designed. The synchronization signal is automatically extracted by the decision feedback method to assist the convergence of equalization, which improves the convergence speed while simplifying the equilibrium calculation. Section 2 present theoretical analyses of the proposed method in detail. Numerical simulations and related discussions are given in Section 3 and 4, respectively, with a conclusion given finally.

II. METHODOLOGY

The OFDM technology has been utilized widely in wired and wireless environments. For instance, in the asymmetric digital subscriber line (ADSL) channel specified in the ITU-992d, the wireless channel specified in the 802.11e, OFDM performs as a fundamental modulation method. As is known, in the wireless channel environment, owing to the influence from multi-path propagation, Doppler shift, free-space transmission loss and fading, the OFDM signals generally suffers the unwanted ISI and ICI, which will consequently increase the bit error rate of the received symbols after demodulation and the difficulty of equalization.

![FIGURE 2. A simplified schematic of the base-band module for an OFDM system.](image)

Figure 2 sketches the simplified schematic of the base-band part for a conventional OFDM system. The serial input binary signal is processed by constellation mapping firstly and then converted into parallel form [14]. Later, after the inverse fast Fourier transformation (IFFT) calculation, the i-th output signal can be expressed as:

\[ X(i) = F_{LN}^H t_s(i). \] (1)

The demodulation of OFDM symbols is sensitive to the carrier frequency offset. If the receiver does not estimate the carrier frequency offset and demodulate the received signal directly, it will not only influence the subsequent carrier synchronization and bit synchronization, but also result in the orthogonality between sub-carriers of the OFDM symbols being destroyed. As a result, the ICI is induced. In the simulation setup, the number of symbols is \(n = 16\); the sampling rate is \(f_s = 4000\) Hz; the carrier frequency is \(f_c = 4\) MHz, and the carrier frequency offset \(\Delta f = 0\) Hz.

Assume that the impulse response of the continuous fading channel is of the form as:

\[ h(\tau, t) = \sum h_p(t) \delta(\tau - \tau_p). \] (2)

where \(\tau_p\) is the multi-path delay and \(h_p\) is the complex gain of the multi-path channel. Then,

\[ h_p(t) = h_p e^{j(\phi + 2\pi ft)}. \] (3)

As the sampling frequency of the receiver is consistent with that of the transmitter, the radio frequency (RF) signal received by the receiver antenna can be expressed as:

\[ y(nT) = \sum h_p(nT) x(nT - \tau_p) + n(nT). \] (4)

Equation (4) is the discrete OFDM sample received by the equalizer. Here, \(h(t)\) can be expressed in various forms, mainly depending on the specific channel environment.

It is well-known that the OFDM modulation can adjust to different channel environments. Here, the proposed blind equalization method in this work is mainly for the wireless time-varying channel environment [15]. And even just in the wireless channel environment, there are various applications using the OFDM modulation, such as the digital audio broadcasting (DAB), the digital video broadcasting (DVB), and the wireless local area network (WLAN) based on the IEEE 802.11 standard. Most of these applications take advantage of the inherent feature of OFDM to partially eliminate the ISI that are caused by the multi-path effect.

A. WIRELESS CHANNEL MODEL

Based on the wave propagation theory, the electromagnetic waves will propagate directly as no obstacles exists in the wireless channel, and this mechanism has been widely used in the satellite communication, deep space communication, and short-range wireless communication. As one object existing in the channel is much larger than the wavelength, the incident electromagnetic waves will be reflected notably. Comparatively, as physical size of the obstacle is comparable with the wavelength, the electromagnetic scattering will be induced by rough surfaces, small targets or the irregularity of wireless channels. Moreover, once the electromagnetic waves are blocked by a surface with a distinctly irregular edge, the secondary wave induced by the blocking surface can propagate round the obstacle, which is also known as diffraction. In the wireless channel, the electromagnetic waves can propagate in different mechanisms like direct propagation, reflection, diffraction and scattering. Meanwhile, there are differences between the received signals on their times of arrival, angles of arrival and power strengthens.

Hence, both magnitude and phase of the received signal might vary rapidly in one symbol period, which will produce the multi-path effect and consequently result in the ISI between adjacent received symbols. Thus, the time-varying channel equalization aims to eliminate such interference.
In the multi-path propagation, the received signal contains various components coming from different propagating paths. Generally, the delay of each path is different, and the component waves from different directions will superimpose the arrival signal of different phases. Therefore, the fast fading that is called as Rayleigh fading will be produced. Once there is a main direct-propagation path in the multi-path, envelope of the received signal will obey the Rice distribution, then such fading is called as Rice fading. Actually, the Rayleigh fading is a unique form of the Rice fading. Besides the multi-path effect of the wireless channel, the relative motion between transmitter and receiver will make the time variation of wireless channel become more obvious. That is to say, the wireless channel is uncorrelated scattering channel. Then, the autocorrelation function of $h(t_1, t)$ can be calculated as:

$$R(t_1, t_2, d_k) = \frac{1}{2} E \{ h(t_1, t + d_k) h^*(t_2, t) \}. \quad (5)$$

For most propagation media, the attenuation and phase shift separately denoted by $t_1$ and $t_2$ are mutually irrelevant. That is $R(t_1, t_2, d_k)$ is uncorrelated. Then, Equation (5) can be simplified as:

$$R(dt, d_k) = \frac{1}{2} E \{ h(dt, t + d_k) h^*(dt, t) \}. \quad (6)$$

In fact, Equation (6) is the correlation function of the delay and time difference of the channel. Later, the correlation function of the frequency and time difference can be similarly defined as:

$$R(df, d_k) = \frac{1}{2} E \{ H(df, t + d_k) H^*(df, t) \}. \quad (7)$$

**B. WIRELESS OFDM SIGNAL**

Another more general approach to the wireless channel modelling is to simultaneously model the channel and equalizer in matrix form in the time domain, rather than in vector form. This approach can provide much clearer definition and description of the time-varying channel in the matrix, and keep the equalization with more design flexibility. In this way, all the channel parameters can be determined by using limited observation data (prior knowledge). And the equalizer design is also just with moderate complexity. However, simultaneously modeling the channel and the equalizer is quite challenging or even difficult in practical applications. To avoid such difficulty, another method is developed based on the basic extended model (BEM). Although the BEM-based method just provides more limited design flexibility, it can also perform well in the wireless channel with both time and frequency selectivity as below:

$$h^p[k, n] = \sum_{q=-Q/2}^{Q/2} e^{i2\pi qN} h(p, q, k), \quad k \in \{0, \ldots, L\}. \quad (8)$$

where $q$ is the Doppler spread coefficient, and $h$ denotes the intensity of the $q$th Doppler component at the $p$th receiving antenna at the $k$th time interval.

For each time interval, the channel model can be represented as the sum of a series of complex exponential with Doppler shifts, so that the total amount of Doppler shift can be controllable, even though large Doppler shifts are introduced into the matrix of the channel model. Such equalizer can be modeled by the BEM, which will an effective time-varying filter as well. For a practical wireless OFDM receiver, the signal fed into the channel equalizer is supposed to be expressed more complexity. In fact, the aforementioned derivation contains plenty of ideal hypotheses. However, in practical applications, there are some important factors related to the synchronization of the OFDM receiver, such as: (1) The sampling clock period of the receiver $T'$ is not equal to the sampling clock period of the transmitter $T$; (2) There is a frequency offset $df_c$ between the carrier frequencies of the receiver and transmitter, whose influence on the received signal can be equivalent as a time-varying phase offset during the time-domain demodulation; (3) There is no unified timing reference frame between the receiver and the transmitter. Therefore, as the receiver removes the guard interval for block interception, there is a timing synchronization error $kT$ between the OFDM symbols.

Hence, by taking influence from the above non-ideal synchronization factors into consideration, the channel model with both time and frequency selectivity can be modified as:

$$y(nT') = \sum_m h(nT' - kT) * x(nT' - t_1) * e^{i2\pi df_c(nT')} + n(nT'). \quad (9)$$

To satisfy Equation (9), an ideal synchronization adjustment mechanism must be contained in the communication system, however, it is too difficult to realize the ideal synchronization adjustment skill in practical receiver. Furthermore, it is essential to figure out that some other non-ideal factors have been assumed to be ideal, including: (1) Length of the channel impulse response (CIR) is limited. And the maximum length of the channel delay is always smaller than the guard interval, so that there is no ISI in the received signal; (2) Multi-path distribution of the channel remains constant over one OFDM symbol period; (3) There is no statistic phase noise between the analog oscillators of transmitter and receiver; (4) The RF analog high power amplifier of the transmitter is ideally linear, thus making the large peak-to-average power ratio (PAPR) of OFDM signals be neglected. Unfortunately, all the assumptions mentioned above are almost impossible to be achieved in practical engineering applications. Therefore, it is essential
to take extra measures through the equalization to make the parameters estimation close to the ideal model as well as possible.

III. COLLABORATIVE BLIND EQUALIZATION METHOD

For the blind equalization methods for OFDM systems, the frequency-domain ones are more commonly used. The frequency-domain methods make the synthesized frequency responses of the equalizer and the channel satisfy the condition of no ISI transmission by modifying the frequency characteristics of the system. On the contrary, the time-domain blind equalization for OFDM is relatively rare. In the time-domain methods, the impulse response characteristic of the system is modified, so that the synthesized impulse response of the equalizer and the channel is able to satisfy the condition of no ISI transmission. In a typical OFDM system, the time-domain equalization is usually carried out by inserting pilot into the transmitted symbols.

In this work, the proposed blind equalization method for OFDM system is based on the collaborative time-frequency domain blind equalization without inserting pilot symbols. Specifically speaking, the proposed collaborative blind equalization method utilizes the scheme of decision feedback equalization, which can exhibit better ISI estimation performance as compared with the linear equalization methods and other equalization structures. The decision feedback equalization mainly consists of a forward filter and a feedback filter, as shown in Fig. 3. Obviously, output of the forward filter is sent into the adder and then fed into the decision circuit. Subsequently, the feedback filter utilizes the output of decision circuit as its input, thus to estimate the interference from the previously detected symbols on the present one. That is, sampled values of the output from the adder are fed back into the adder to cancel the interference from the training.

FIGURE 3. Simplified schematic of the proposed blind equalizer based on decision feedback equalization.

Assume that the weight vector $w(k)$ of the blind equalizer has a good initial value. Thereafter, convolution of the channel response and the impulse response of the equalizer can be decomposed into a sum of a correct component and an ISI component. By convolving this joint convolution result with the input signal together, the ISI residual terms and the additional noise (also convolutional noise) can be produced. Moreover, by applying the central limit theorem, it can be proved that the additional noise can be directly modeled and simulated as the Gaussian white noise. Afterwards, the input signal $a(k)$ is independent and identically distributed, and the input signal and convolutional noise are statistically independent. Therefore, the mean square error (MSE) estimation of $a(k)$ is equivalent to the estimation function $K$. Meanwhile, since $a(k)$ obeys the non-Gaussian distribution, its estimation is a nonlinear function that is output by the blind equalizer. Thus, the prior error $e(n)$ is the very difference between outputs of the estimation function and the equalizer. Then, the prior random gradient algorithm of the blind equalizer can be derived as:

$$w(k) = w(k - 1) + u_y(k) e^*(k).$$ (10)

Here, $u$ is the step factor. In fact, this formula is the general form of the LMS blind equalization algorithm.

The proposed blind equalization method is developed on the basis of the normalized LMS (NLMS) method and the recursive least squares (RLS) method, while the LMS and NLMS methods are proposed based on the steepest descent method [16], [17]. First of all, an initial weight value is given. Then, the weight value is gradually changed along the opposite direction of the gradient. Later, the weight vector will eventually converge to the optimum value under some certain conditions. For the LMS blind equalization algorithm, the training-sequences are taken placed by the output of the decision circuit in the receiver. And the convergence rate can be improved by utilizing the decision feedback scheme. Since the LMS blind equalization algorithm is simple, easy to be implemented, it has been utilized widely in various applications and can be used as the reference of other algorithms. The decision error function of the LMS algorithm can be expressed as:

$$e_k = d_k - X_k^T W_k.$$ (11)

Therefore, the partial derivative of the MSE to the weight can be expressed as:

$$\hat{\nabla}_k = \frac{\partial e_k}{\partial W} = \begin{bmatrix} \frac{\partial e_k^2}{\partial w_0} \\ \frac{\partial e_k^2}{\partial w_1} \\ \vdots \\ \frac{\partial e_k^2}{\partial w_L} \end{bmatrix} = 2e_k \begin{bmatrix} \frac{\partial e_k}{\partial w_0} \\ \frac{\partial e_k}{\partial w_1} \\ \vdots \\ \frac{\partial e_k}{\partial w_L} \end{bmatrix} = -2e_k X_k.$$ (12)

On the other hand, the conventional LS and its associated RLS methods have been regarded as the optimum filters for the known data. With the RLS approximation, the same optimum filter will be derived for different datasets. More exactly, the RLS filter can derive the optimal coefficients by processing the datasets of finite length with the time-domain averaging method. Once the input data process is stationary and ergodic, performance of the RLS filter will approach that of the MMSE filter with the data length increasing. Hence, the error function $e(n)$ can be expressed as sum of the products of element values of the weight vector and the corresponding
values of the signal:

\[ e(1) = d(1) - w_1(n)x(1) - w_2(n) \cdot 0 - \cdots - w_M(n) \cdot 0 \]
\[ e(2) = d(2) - w_1(n)x(2) - w_2(n) \cdot x(1) - \cdots - w_M(n) \cdot 0 \]
\[ \vdots \]
\[ e(M) = d(M) - w_1(n)x(M) - \cdots - w_M(n)x(1). \]  

(13)

In practical applications, a small step factor \( u \) is helpful to reduce the gradient noise of the algorithm; however, it will decrease the convergence rate as well. On the other side, enlarging the value of \( u \) will enhance the offset coefficient and gradient noise. Hence, selecting the proper value of \( u \) is important for the overall performance of the algorithm. The conventional LMS and its improved forms are all with small amount of calculation and easy-implementation, which has been regarded as their most prominent advantage over the LS and RLS algorithms. Therefore, the LMS algorithm has been widely utilized for the OFDM blind equalization applications. More recently, with the rapid development of the large-capacity, high-speed processing chips, and the emergence of fast batch processing algorithms, the RLS algorithm can also be used in the high-speed data transmission in the fast-changing channels. Based on the aforementioned analyses, a collaborative algorithm combining the NLMS and RLS together is proposed in this work for the blind equalization application of the OFDM systems in wireless channels. Furthermore, since the gain matrix \( C_m \) of the RLS algorithm is an \( M \times M \) matrix, calculation of the matrices multiplication will be quite complex and massive. To overcome this issue, a simplified method for calculating the inverse matrix of \( C_m \) is also developed:

\[ u(n) = X_m^T(n) \cdot C_m(n) \cdot X_m(n). \]  

(14)

\[ C_m(n+1) = C_m(n) + 2 \cdot K \cdot e(n). \]  

(15)

\[ e(n) = D(n) - X_m^T(n) \cdot W_m(n). \]  

(16)

\[ g_m(n) = C_m(n) \cdot X_m(n)/[\lambda + u(n)]. \]  

(17)

\[ W_m(n+1) = W_m(n) + g_m(n) \cdot e(n). \]  

(18)

Here, \( D(n) \) is the decision symbol and \( e(n) \) is the estimated decision error after iteration. \( K \) is a very large constant. Thus, in the decision feedback framework, the output of the system with the blind equalization structure is:

\[ Y_m(n) = W_m(n) \cdot X_m^T(n) - V_y(n) \cdot \hat{Y}_m(n). \]  

(19)

\[ V_m(n) = V_m(n-1) - u(n) \cdot \hat{e}(n) \cdot Y_m(n-1). \]  

(20)

Here, \( V(n) \) is the tap coefficient of the decision feedback filter. \( \hat{e}(n) \) is the actual error generated by the system after decision, which can be expressed as:

\[ \hat{e}(n) = D(n) - SYN(n). \]  

(21)

where \( SYN(n) \) is the pilot signal of the feedforward filter section.

In the proposed method, the NLMS algorithm is used to update the gain matrix of the RLS algorithm, so as to simplify the calculation and improve the convergence rate. Since the proposed method simultaneously takes advantages of the conventional NLMS and RLS algorithms, it can be called as LM-RS algorithm. Subsequently, with the proposed LM-RS algorithm, an equalizer with simple structure is developed, which generates a synchronization sequence by the decision scheme firstly and then feed back to the front-end of the equalizer for the further calculation.

Figure 4 gives block diagram of the blind equalizer based on the proposed LM-RS algorithm, in which the carrier synchronization is omitted. As shown in Fig. 4, with the synchronization (SYN) bytes, the bit synchronization is carried out and the blind equalization is performed on each OFDM symbols. The received time-domain signals are transformed into the frequency domain by utilizing the fast Fourier transform (FFT), followed by the blind equalization, since the decisions of OFDM symbols are supposed to be carried out in the frequency domain. Then, blind decision is operated on the frequency-domain signals coming from the blind equalizer. Afterwards, the frequency-domain SYN sequences are generated by the demodulation, and the optimum frequency-domain SYN sequence is further obtained based on the MMSE principle. By operating the IFFT process on the optimum frequency-domain SYN sequence, the time-domain SYN sequence can be achieved for the subsequent time-domain equalization. The specific realization procedures of the algorithm are sketched in Fig. 5. Obviously, the bit synchronization is operated at the time domain, while the decision is operated at the frequency domain, as well as getting the SYN header. Hence, the FFT and IFFT processes are quite important for the proposed LM-RS blind equalization algorithm.

**IV. NUMERICAL SIMULATION DEMONSTRATION**

To verify the availability and effectiveness of the proposed LM-RS algorithm, some numerical simulations have been carried out. The multipath fading channel is used as the time-varying channel model, and number of its fundamental function is 5. The main simulation parameters of the time-varying channel is listed in Table 1.
First of all, Fig. 6 shows the simulated normalized MSE (NMSE) and cumulative error of the algorithm for each iteration. In the simulation setup, order of the equalizer is set to 18, the channel is a 7th-order multi-path channel, and number of the transmitted OFDM complex sequence is 5000. It can be obtained from Fig. 6 that the NMSE is smaller than 0.075 for all numbers of iteration, which is quite low. Actually, for most cases, the simulated NMSE is below 0.05. This also illustrates that the proposed LM-RS algorithm exhibits fast convergence rate. Moreover, the cumulative error performance also exhibits strict monotonic-increasing characteristic. That is, with the number of iteration getting larger, the cumulative error becomes higher as well. Such monotonic-increasing characteristic demonstrates that the proposed LM-RS blind equalization algorithm is with good stability.

Subsequently, to demonstrate the advantages and disadvantages of the proposed LM-RS algorithm over the conventional NLMS and RLS algorithms, some extra simulations have been done. It is essential to emphasize that, to compare the aforementioned three algorithms reasonably, the same simulation conditions are applied. That is, the same blind equalizer structure shown in Fig. 4 is used for the three algorithms, as well as the parameters setup. Simulated equalization NMSE and cumulative error of the conventional NLMS and RLS algorithms are given in Fig. 7. As shown in Fig. 7(a), the equalization NMSE of the NLMS algorithm is below 1 for all numbers of iteration, which is much higher than that of the proposed LM-RS algorithm. However, this still represents a relative fast convergence rate. Meanwhile, it can...
be captured that equalization NMSE of the NLMS swings quite heavily within the change of number of iteration. While for the proposed LM-RS case, swinging of the equalization NMSE is much slighter. Another drawback of the conventional NLMS algorithm is that, with the number of iteration from 900 to 1800, and over 3000, the cumulative error will change heavily, breaking the original monotonic increasing characteristic. This unwanted phenomenon indicates that the NLMS algorithm is with poor stability.

Hence, its performance might be unstable in practical applications. On the other side, for the RLS case, the error performance is much different. According to Fig. 7(b), the largest equalization NMSE of the RLS algorithm is over 0.2 for some unique numbers of iteration. Whereas, as the number of iteration changes, equalization NMSE of the RLS algorithm swings a bit more heavily (from 0 to 0.05) than that of the proposed LM-RS algorithm, which is much better than the NLMS case. Moreover, the RLS algorithm shows quite good stability owing to its cumulative error is strictly monotonic increasing, which seems even a bit better than its corresponding LM-RS counterpart. Hence, it can be easily obtained from Fig. 6 and 7 that, with the same blind equalizer structure given in Fig. 4, the proposed LM-RS algorithm achieves the best equalization NMSE performance over the conventional NLMS and RLS algorithms, as well as similar cumulative error performance as the RLS case.

![Comparison of the steady-state errors between the LM-RS and RLS algorithms.](image)

FIGURE 8. Comparison of the steady-state errors between the LM-RS and RLS algorithms.

Thirdly, as indicated in Section 2, $K$ is an important parameter for the overall performance of blind equalization algorithms. Hence, to realize the advantage of the proposed LM-RS algorithm, its performance associated with the parameter $K$ is further studied. Figure 8 sketches the steady-state error of equalization of the proposed LM-RS and the conventional RLS algorithms. Obviously, as $K$ increases, the conventional RLS algorithm exhibits extremely stable steady-state error of equalization (actually the steady-state error of RLS almost keeps unchanged around $1.5 \times 10^{-2}$). For the proposed LM-RS algorithm, as the value of the $K$ factor increases, the steady-state error of equalization becomes smaller firstly and then keeps stable gradually. Particularly, as $K \geq 4 \times 10^6$, the steady-state error of the proposed LM-RS algorithm will be smaller than that of the conventional RLS algorithm. Moreover, as $K \geq 4 \times 10^6$, the steady-state error of the proposed LM-RS algorithm will be around $4 \times 10^{-3}$ to $5 \times 10^{-3}$, which is nearly triple times smaller than that of the RLS algorithm. Therefore, by selecting the value of $K$ properly, the proposed LM-RS blind equalization algorithm will exhibit better steady-state error performance. In practical applications, it is better to make the value of $K$ a bit larger, around $1 \times 10^{10}$, as shown in Fig. 8.

Afterwards, for the specific OFDM system application, the utilized blind equalizer and its associated equalization algorithm might exhibit different performance owing to the probable influence from the unique characteristics of OFDM. Hence, effectiveness of the proposed LM-RS algorithm on the blind equalization of OFDM system is further studied deeply. Meanwhile, the overall performance of the conventional RLS algorithm on the blind equalization of OFDM system is discussed as well, thus to provide a frame of reference to evaluate the performance of the proposed LM-RS algorithm reasonably and convincingly. In the simulation setup, the time-varying wireless channel is utilized, and the quadrature amplitude modulation (QAM) is then employed to the base-band signals of OFDM system. Particularly, to provide better comparison between the conventional RLS and the proposed LM-RS blind equalization methods, modulations of various orders, including 4QAM, 16QAM and 64QAM, are utilized in the OFDM system one by one. As is known, 4QAM with fixed amplitude only contains phase modulation, which can be regarded as the very quadrature phase shift keying (QPSK) modulation. Moreover, number of the transmitted base-band symbols for simulation is 7000, with a signal-to-noise ratio (SNR) of 13.35 dB and a symbol rate ($R_s$) of 10 Mbaud. Furthermore, the transmitter utilizes up-sampling by a factor ($p_{us}$) of 16, and the sampling frequency ($f_s$) in the receiver is 40 MHz.

By separately adopting the conventional RLS and the proposed LM-RS blind equalization methods to QAM signals of various orders in the OFDM system, the output constellations are shown in Fig. 9. For the simplification of simulation and comparison, QAM signals of all orders are set with square constellations. The output 4QAM signal constellations without any blind equalization, with the conventional RLS algorithm, and with the proposed LM-RS algorithm are listed in Fig. 9(a), 9(b), and 9(c), respectively. First of all, as shown in Fig. 9(a), before the blind equalization process, the four constellation areas of 4QAM signal are disorderly and irregular, exhibiting large dispersion and indicating extremely high symbol error rate ($P_e$) after demodulation. Secondly, according to Fig. 9(b), with the conventional RLS blind equalization method, the constellation dispersion of the 4QAM signal is pretty low, owing to the four constellation areas being able to be separated easily. On the other hand, from Fig. 9(c), the constellation dispersion with the proposed LM-RS blind equalization method is
FIGURE 9. Simulated constellations of the received signal with the conventional RLS and the proposed LM-RS blind equalization methods. (a) 4QAM without equalization; (b) 4QAM with RLS; (c) 4QAM with LM-RS; (d) 16QAM without equalization; (e) 16QAM with RLS; (f) 16QAM with LM-RS; (g) 64QAM without equalization; (h) 64QAM with RLS; (i) 64QAM with LM-RS.

quite small as well. Moreover, the output constellation with the proposed LM-RS algorithm exhibits vertically-squeezing effect so that each constellation area appears in ellipse shape. As shown in Fig. 9(c), each constellation area ranges from \(0\) to \(2\), namely 0 to 2 for positive axis and 0 to \(-2\) for negative axis, along the in-phase direction. While it only covers from \(0.5\) to \(1.5\) along the quadrature direction. With such ellipse-shaped constellation, the demodulated \(P_e\) along the in-phase direction will be much higher than that along the quadrature direction. Meanwhile, it can also be predicted that, for the demodulated 4QAM signal, the amplitude of its in-phase component is most likely larger than that...
of its quadrature component. Furthermore, for other QAM cases, similar results can be captured. For instance, Fig. 9(d) and 9(g) separately shows the 16QAM and 64QAM signal constellations without blind equalization, in which terrible dispersion effect exists. The constellation dispersion of 64QAM is even much heavier than the 16QAM case, as all adjacent constellation areas overlap with each other and the whole constellation appears as an entire square shape. Then, for Fig. 9(e) and 9(h), the conventional RLS blind equalization method exhibits good performance for both the 16QAM and 64QAM signals, since each constellation area is in circular shape and can be easily sorted out from its neighborhoods. Moreover, as depicted in Fig. 9(f) and 9(i), by applying the proposed LM-RS blind equalization method to the simulated 16QAM and 64QAM signals in OFDM system, the output constellations are quite good as well, with the 16 constellation areas of 16QAM and the 64 constellation areas of 64QAM being clear enough. Meanwhile, it can be also obtained from Fig. 9(f) and 9(i) that all constellation areas with the proposed LM-RS algorithm is squeezed into ellipse shape. Therefore, after the demodulation process, the in-phase $P_e$ will be higher than the quadrature one. Additionally, according to Fig. 9(c) and 9(f), for the 4QAM and 16QAM with the proposed LM-RS algorithm, all constellation areas clock-wisely rotate a small angle, while for the 64QAM case in Fig. 9(i), the rotating effect of constellation is not notable enough. Generally, such negative rotating effect will probably worsen the overall $P_e$ performance of the demodulated signals. Fortunately, by adjusting the value of $K$, the proposed LM-RS blind equalization method will achieve an improved $P_e$. Actually, by considering Fig. 8 and 9 together, it can be captured that: for most values of $K$, both the steady-state error and the $P_e$ of the proposed LM-RS blind equalization are separately close to their corresponding conventional RLS counterparts.

Moreover, the equalization error and cumulative error performance of the NLMS, RLS and LM-RS blind equalization methods for the 4QAM signal of the OFDM system in time-varying and fading wireless channel are studied as well, with the simulated results listed in Fig. 10. According to Fig. 10(a), as the number of iteration is larger than 300, the equalization error of the conventional NLMS blind equalization method is below 3, showing good convergence rate. And the associated cumulative error is monotonic-increasing greatly, exhibiting that the NLMS method has quite strong stability. For the RLS case in Fig. 10(b), the equalization error can be larger than 50 and swing heavily with the number of iteration smaller than 500. As the number of iteration is over 500, the equalization error is below 4. However, the cumulative error of the RLS method is not strictly monotonic increasing for all numbers of iteration. Particularly, as the number of iteration is larger than 750, the cumulative error will swing extremely heavily between $2 \times 10^3$ and $1 \times 10^4$. That is, as the number of iteration gets larger, the error performance of the RLS method will become unstable. Later, as shown in Fig. 10(c), distribution characteristics of the equalization error of the LM-RS method is quite interesting.
almost monotonic increasing. Whereas, with the number of iteration increasing over 1050, the cumulative error becomes swinging between $3 \times 10^3$ and $1 \times 10^4$. These results show that the LM-RS method is able to converge much more quickly than the conventional NLMS and RLS methods, whereas its stability is relatively poor. In addition, by comparing Fig. 10(a), 10(b) and 10(c) together, it can be summarized that the proposed LM-RS and the conventional NLMS methods are with much faster convergence rate than the conventional RLS method.

Afterwards, for blind equalization algorithms, the amount of calculation and computational complexity are performance metrics of significant importance as well. To evaluate these metrics, some further analyses are carried out to the proposed LM-RS method, along with the conventional LMS, NLMS and RLS blind equalization methods for reference. Table 2 shows comparison of computational complexities between the proposed LM-RS and the four aforementioned conventional methods. Obviously, the LMS and NLMS methods are with computational complexities of $N$-level on both additions and multiplications in one iteration, where $N$ denotes order of the filter utilized in the blind equalization. Whereas, for the RLS and LM-RS algorithms, the computational complexity on additions and multiplications in one iteration are both of $N^2$-level, which are much larger than the LMS and NLMS cases. The NLMS method requires more calculation steps than the LMS one, which is mainly attributed from the normalization process. Moreover, it can be further obtained from Table 2 that the proposed LM-RS method achieves reduction in computational complexity over the conventional RLS method. To demonstrate such reduction more definitely and concretely, detailed computational complexities of the conventional RLS and the proposed LM-RS methods are further calculated. Number of calculations in one iteration of the RLS and LM-RS methods with various filter order $N$, including additions and multiplications, are listed in Table 3, respectively. As compared with the conventional RLS algorithm, even the filter utilized in blind equalization is just with an order of 2, the proposed LM-RS method can achieve calculation reductions of 7.7% for addition and 42.8% for multiplication, respectively. More excitingly, with the filter order $N$ getting larger and larger, the calculation reduction in both addition and multiplication will increase higher and higher, as shown in Table 3. Particularly, once

| Method     | Number of additions in one iteration | Number of multiplications in one iteration |
|------------|-------------------------------------|------------------------------------------|
| LMS        | $2N$                                | $3N$                                     |
| NLMS       | $3N$                                | $4N$                                     |
| RLS        | $4N^2-1$                            | $5N^2+4N$                                |
| Proposed LM-RS | $3N^2+N$                          | $2N^2+3N^2+2N$                          |

$N$ denotes order of the filter utilized in the blind equalization method.

The filter order beyond 6, over 20% reduction in addition and 55% reduction in multiplication can be acquired by the proposed LM-RS method over the conventional RLS one. Hence, the proposed LM-RS method is more suitable for the blind equalization processing in OFDM systems with limited hardware resources, which is much more preferred in practical engineering applications.

Thereafter, to verify the performance improvement of the proposed LM-RS algorithm, some further comparisons have been made. Table 4 sketches the BER reduction of the proposed LM-RS algorithm over the conventional NLMS and RLS methods in one iteration with the identical SNR of 10dB and various filter order $N$. Meanwhile, to evaluate error performance of the LM-RS method more convincingly and reasonably, the popular variable step-size NLMS (VSS-NLMS) and hierarchical RLS (HRLS) blind equalization algorithms, are simultaneously included for comparison as well [19], [20]. Firstly, as the filter order $N$ gets higher an higher, BER reduction achieved by the proposed LM-RS method also becomes larger and larger gradually. Therefore, utilizing higher-order filter is helpful to improve the BER performance. Secondly, according to Table 4, the proposed LM-RS method can achieve larger BER reduction over the conventional RLS method, whereas it only acquires less BER performance improvement as compared with the VSS-NLMS algorithm [21]–[23]. Moreover, to the conventional NLMS

| Filter order (N) | BER Reduction |
|------------------|---------------|
|                  | NLMS | VSS-NLMS | RLS | HRLS |
| 2                | 1.3% | 1.2%     | 1.8%| 1.5% |
| 6                | 2.1% | 1.9%     | 3.8%| 3.2% |
| 10               | 3.5% | 2.3%     | 4.3%| 4.2% |
| 14               | 4.5% | 3.7%     | 5.5%| 4.8% |
| 18               | 5.2% | 4.5%     | 6.8%| 5.8% |

All results are calculated for the same SNR of 10 dB.
and HRL cases, the LM-RS method shows medium improvement on error performance. Last but not the least, as compared with the four aforementioned conventional blind equalization methods, the proposed one achieves a bit of BER reduction, which illustrates better overall error performance.

Table 5 shows numbers of iterations for convergence of various blind equalization methods with the same BER and various filter orders. Meanwhile, the improvement on convergence rate of the proposed LM-RS method over the conventional algorithms are also given. Particularly, the improvement on convergence rate is calculated as below:

\[
P_{\text{imp}} = \frac{N_x - N_{\text{LM-RS}}}{N_x} \times 100\%.
\]

where \(P_{\text{imp}}\) is the improvement on convergence rate of the proposed LM-RS method over other conventional ones. \(N_x\) is the number of iteration for convergence of the conventional blind equalization methods. \(N_{\text{LM-RS}}\) is the number of iteration for convergence of the proposed LM-RS method.

As shown in Table 5, for the proposed LM-RS and the conventional NLMS, VSS-NLMS, RLS and HRLS methods, the higher the filter order is, the larger the number of iterations for convergence is. That is, higher-order filter needs more iterations for convergence. Moreover, for the same filter order and same BER, the conventional NLMS method has the largest number of iterations for convergence, followed by the conventional VSS-NLMS, RLS and HRLS methods with gradually decreased numbers of iterations for convergence [24], [25]. And the proposed LM-RS method is with the least number of iteration for convergence. Exactly speaking, as compared with the conventional NLMS and VSS-NLMS methods, the proposed LM-RS one is able to achieve an improvement on convergence rate of 16.6% or more. On the other hand, as compared with the RLS-type methods, i.e. the RLS and HRLS, the proposed LM-RS method can acquire an improvement on convergence rate of few percent as well [26], [27]. Therefore, it can be easily captured from Table 5 that the proposed LM-RS method is with the fastest convergence rate as compared with the aforementioned conventional methods.

In a word, by considering Table 2, 3, 4 and 5 together, it can be easily summarized that the proposed LM-RS blind equalization method is able to exhibit similar (or even better) BER performance and quite faster convergence rate than the conventional NLMS, VSS-NLMS, RLS and HRLS ones, as well as much lower computational complexity than the RLS case.

Finally, Fig. 11 gives the NMSE and BER performance of the NLMS, RLS and LM-RS methods versus various SNR of the received signal, as well as different filter order \(N\) and interference factor \(p\). To simplify the performance comparison, all numerical simulations are carried out under the identical initial setups, i.e. 4QAM signal with the OFDM system in the time-varying and fading channel. First of all, as shown in Fig. 11, for all cases, with SNR of the received
signal increasing higher, the NMSE and BER of the five aforementioned methods all move downward. Therefore, for the wireless communication system, improving SNR of the transmitted signal is helpful to enhance the overall transmission performance significantly. Subsequently, as shown in Fig. 11(a), for the same SNR and $N$, the NLMS method is with the largest NMSE, following with the VSS-NLMS, RLS and HRLS methods in turn, while the LM-RS method exhibits the smallest and best NMSE performance. Meanwhile, as $N$ becomes larger, all the five methods can achieve smaller NMSE. Moreover, according to Fig. 11(b), for $p = 0.5$, whatever the SNR is large of small, the NLMS algorithm always exhibits the largest NMSE, while the LM-RS one performs the smallest NMSE. For the VSS-NLMS, RLS and HRLS cases, their NMSE values are medium, smaller than that of the NLMS method but larger than that of the LM-RS one. Particularly, as SNR is less than 3 dB, the VSS-NLMS and RLS algorithms achieve similar NMSE performance, which is worse than that of the HRLS one. Whereas, as SNR is over 3 dB, the RLS method will exhibit better NMSE than its corresponding VSS-NLMS counterpart but still worse than the HRLS case. On the other hand, for $p = 0.1$, the LM-RS method achieves the best NMSE performance, while the HRLS method exhibits larger NMSE and the RLS method even shows a larger one. Fortunately, these three methods are all with better NMSE, performance than the VSS-NLMS and NLMS cases.

Meanwhile, another interesting result can be obtained from Fig. 11(b): The VSS-NLMS method can achieve better NMSE performance than the NLMS method with a smaller SNR below 8.5 dB, while the situation will be opposite with a larger SNR over 8.5 dB. Furthermore, as $p$ gets smaller, all the five aforementioned methods will achieve smaller NMSE, which can decrease quickly with the SNR increasing as well. Hence, it can be easily captured from Fig. 11(b) that the proposed LM-RS method can exhibits the best NMSE performance over the other fours. And to ensure the NMSE performance of the proposed LM-RS method, as well as the other fours, a small $p$ is much preferred. In addition, for the situation of SNR $< 11$ dB, the proposed LM-RS method with a larger $p$ can achieve better NMSE than the NLMS and VSS-NLMS ones that are with a smaller $p$. And for the situation of SNR $< 6$ dB, the LM-RS method with a larger $p$ will even be better than the RLS method with a smaller $p$. Therefore, the proposed LM-RS method is more robust and suitable for the poor transmission conditions. This characteristic is unique but potentially important. For instance, in practical application that is with large interference factor, the SNR is probably terrible either. Then, the proposed LM-RS method will be much more preferred than other fours. Finally, from the BER in Fig. 11(c), for the same SNR and $p$, the NLMS type methods, including the NLMS and VSS-NLMS, show the worst BER performance while the LM-RS method exhibits the best. The RLS type methods, namely the RLS and HRLS, acquire medium level of BER performance. As SNR gets larger or $p$ gets smaller, BER values of the five methods will all decrease. Particularly, BER of the NLMS method with $p = 0.1$ can be even smaller than that of the LM-RS method with $p = 0.5$. Hence, the interference factor $p$ has significant influence on the overall BER performance. In a word, with larger SNR and $N$, as well as smaller $p$, the proposed LM-RS method will achieve the best NMSE and BER performance over the conventional NLMS, VSS-NLMS, RLS and HRLS methods.

### V. CONCLUSION

This work presents a collaborative blind equalization method for the multi-carrier modulation OFDM signals in the time-varying wireless channel. A modified blind equalizer structure is developed for the OFDM systems firstly, which utilizes the optimum demodulation synchronization sequence to operate the decision feedback, thus to speed up the convergence of time-domain equalization of OFDM signals. Based on this modified equalizer structure, the LM-RS blind equalization algorithm for OFDM signal is proposed, which has been significantly improved on the indicators of steady-state error and convergence rate. The comprehensive analysis has demonstrated that the proposed equalizer structure is more suitable for the blind equalization of OFDM signals. Furthermore, the proposed LM-RS blind equalization method might perform fast convergence rate for the QAM signals in OFDM systems with the time-varying channel, exhibiting better performance than the conventional frequency-domain equalizations. For instance, numerical simulations have shown that the proposed LM-RS blind equalization method can achieve over 16.6% convergence rate and better BER performance than the conventional NLMS-type methods. Moreover, with the filter order $N$ getting larger than 6, calculation reductions of over 20% in addition and over 55% in multiplication.
as well as better BER performance and faster convergence rate, can be simultaneously achieved by the proposed LM-RS method over its corresponding conventional RLS counterpart.

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