A Concurrent Dual Mode Adaptive Switching Blind Equalization System in Impulse Noise

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Abstract. Due to the influence of various factors, the noise in actual digital communication system is non-Gaussian and always assumed to be impulse noise. But most blind equalization algorithms are mainly directed against Gaussian noise and the performance of common algorithms under impulse noise is poor. So, in this paper, we have studied the problem of channel equalization under impulse noise and improved the fractional lower order constant modulus algorithm (FLOM-CMA). Then, by convex combining with decision-directed least mean p norm (DD-LMP) algorithm, a new concurrent adaptive switching blind equalization system had been proposed here. The advantages of different modes are fully combined in our system by soft-switching, which is the FLOM mode is used to make the equalization process converge quickly, and then, after the eye map of signal is open, the joint parameter is gradually reduced to zero and our system adaptive switching to DD mode to improve its convergence accuracy. The excess mean square error (EMSE) of our system is analyzed, and several experiments have been simulated to prove that our system performs better than other traditional algorithms.

1. Introduction

Due to the influence of imperfect characteristics such as channel multi-path effect, and frequency selective fading, the received signals often has serious inter-symbol interference (ISI). In order to overcome the influence of ISI, the blind equalization algorithm is always used in high-speed digital communication systems. Also, as an important mean of improving the communication quality and reducing the bit error rate (BER), blind equalization algorithm no need for training sequence which means the system bandwidth could be maximum utilized. Meanwhile, for non cooperative communication, blind equalization is a necessary step to restore the transmitted signals [1-3].

As the most classic blind equalization algorithm, the constant modulus algorithm (CMA) is one of the most widely used blind equalization algorithms [4-5]. On this basis, the modified constant modulus algorithm (MMA) is more suitable for channel equalization with phase rotation [6][7]. In recent years, many scholars have made improvements by combining CMA or MMA with the adaptive filtering algorithm such as decision-directed least mean square algorithm (DD-LMS) [8-10]. But most of them are based on the analysis of Gauss noise environment. Actually, because of the influence of thunderstorm, electromagnetic interference and human factors, the received signals is often accompanied by strong irregular pulse characteristics, and the noise environment does not conform to the Gauss distribution. The scholars have found that the -stable distribution model has the characteristics of thick trailing and
irregular impulse, and satisfies the generalized central limit theorem, which is more suitable for the actual noise environment [11][12].

It is worth noting that there is no generalized second order moment in -stable distribution, so the fractional lower order constant modulus algorithm(FLOM-CMA) has been proposed in Ref. [13]. The algorithm can effectively suppress impulse noise, but similar to CMA, it has some disadvantages such as: can not correct phase rotation and the poor convergence accuracy. To overcome this disadvantages, a modified FLOM-CMA has been proposed by modifying the cost function[14], but the convergence accuracy is still low. In order to get better convergence speed and accuracy, the quadratic distance between the probability density function of output and desired signals has been introduced[15]. And then, combined with a set of Dirac-delta functions, the blind equalization algorithm has the effect of cutting out the outliers on the difference between the desired level values and impulse-infected outputs[16][17]. However, since the amplitude of the signal is not used, the phase of the balanced signal has been randomly rotated, and also, it is very sensitive to noise. It is well known that the biggest contradiction of multimode blind equalization algorithm is the contradiction between convergence speed and steady-state residual error after convergence[9]. Considering that the single algorithm can not meet the requirement of convergence accuracy and convergence speed simultaneously. Ref. [18] proposed a concurrent double mode algorithm based on FLOM-CMA and decision-directed least mean p norm(DD-LMP). By introducing the ‘stop-and-go’ method to control whether the weight vector of DD-LMP is updated or not. The phase rotation of the signal is corrected effectively, but the hard switching way may bring convergence error jitter.

In this paper, we propose a novel adaptive switching blind equalization algorithm by convexly combining the improved FLOM-CMA and DD-LMP algorithm. Our aim is to make full use of the advantages of fast convergence of FLOM-CMA and low steady-state error of DD-LMP. The way of combination in our system is to ensure that the performance of the whole system is always consistent with the better one. In the initial stage of equalization or the abrupt changes of the channel parameters, the system adaptive updates the joint parameter to make sure the system is working in the improved FLOM-CMA mode. When the eye-map of receiving signal is sufficiently open, the over all system switch to the DD-LMP mode and the steady-state MSE of the system is further reduced. Similar to the convex combination of adaptive filters[19][20], The joint parameter in our work is computed according to the whole system error.

The main improvement of the proposed system include:

The original FLOM-CMA algorithm is improved by a modified cost function both consider amplitude and phase information of the transmission signal. The new calculate way of modulus value is divided into two parts: the virtual part and the real part. The improved algorithm is effective in correcting the phase rotation.

Unlike other algorithms for mixing different kinds of filters, our system consider the mix of equalizer with two types of operation mode in impulse noise. So, the two equalizers should not adapted independently and the mixing parameter should consider the supervised element in the mixture[9].

The two blind equalizers switches smoothly, avoiding the error caused by the decision error in the traditional hard-switching mode. At the same time, there is no need to set a threshold value, and it also avoids the poor equalization performance caused by inaccurate threshold setting.

As we all know, the previous analysis methods of excess mean square error(EMSE) are no longer in effective in impulse noise. And it is a challenging task to compute the system EMSE. We have introduced the energy conservation arguments to analysis the tracking performance of both improved FLOM-CMA and DD-LMP, and then the cross-EMSE which is generated by convex combination of two equalizers is calculated.

The paper is organized as follows. In Section II, we have described the problem of blind equalization and analyzed the characteristics of impulse noise model briefly. In Section III, the improved FLOM-CMA equalizer is discussed, and then, a novel concurrent dual mode adaptive switching blind equalization algorithm based on FLOM-CMA and DD-LMP is proposed. Section IV have analyzed the steady-state characteristics and the approximate analytic expression of EMSE of the combined system.
is deduced. By considering different situations, the performance of the proposed algorithm and several other blind equalization algorithms are compared in Section V, and the simulation results are proposed. Then the conclusion is drawn in Section VI.

2. The Proposed Concurrent Equalizer

2.1. The principle of convex combination

In this paper, we propose a concurrent adaptive switching blind equalization system based on improved FLOM-CMA and DD-LMP algorithm. The concept of convex combination of adaptive filter is introduced here to improve the convergence speed and convergence accuracy of blind equalization algorithm under the SoS noise. Specifically, the equalization system structure is given in Figure 2.

In our system, we achieve the convex combination between two algorithms by introducing joint parameters \( \hat{a}(n) \in [0,1] \), so the output of the whole system can be expressed as:

\[
y(n) = y_1(n) \hat{a}(n) + y_2(n) [1 - \hat{a}(n)]
\]

(1)

Where \( y_i(n) = w_i^T(n)x(n), i = 1,2 \) are the output of improved FLOM-CMA (when \( i=1 \)) and DD-LMP (when \( i=2 \)), respectively. And the length of weight coefficient \( w_1(n) \) and \( w_2(n) \) both are M. So the overall system weight vector is:

\[
w(n) = w_1(n) \hat{a}(n) + w_2(n) [1 - \hat{a}(n)]
\]

(2)

Because there is no training sequence in blind equalization system, we assume that the output of the decision device \( \hat{a}(n - \Delta) \) is approximate to the source sequence. Assume \( s_i \) is the nearest point to \( y(n) \), then[18]:

\[
\hat{a}(n - \Delta) = Q[y(n)] = \arg \min_{s_i \in S} |y(n) - s_i|^2
\]

(3)

so the output error is \( \epsilon(n) = \hat{a}(n - \Delta) - y(n) \). Our goal is to ensure that \( \hat{a}(n) \) is approaching to 1 at the beginning of equilibrium, and the system works in the FLOM mode to achieve fast equalization. When the system error gradually decreases, \( \hat{a}(n) \) automatically decreases at the same time, and finally approach to 0, then it works in the DD mode to makes higher precision. Through this soft switching way, we achieve the goal that the system always works in the best effect mode. According to [19-21], \( \lambda(n) \) is update by gradient descent method and usually use an auxiliary parameter \( \epsilon(n) \) to adjust.

\[
\lambda(n) = \text{sgm}[\epsilon(n)] = \frac{1}{1 + e^{-\epsilon(n)}}
\]

(4)

Thus, the gradient descent method is used to update \( \epsilon(n) \) too[21].

\[
\epsilon(n + 1) = \epsilon(n) + \mu_{\epsilon} \text{Re} \{ \epsilon(n)[y_1(n) - y_2(n)]^T \lambda(n)[1 - \lambda(n)] \}
\]

(5)

Where \( \mu_{\epsilon} \) is the step-size of auxiliary parameter. Using the sigmoidal activation function to assist iterative \( \lambda(n) \) can make it change more smoothly near 0 or 1, so that, the switch of equalizer is more smoother. To ensure the convergence of the system, Eq.8. cannot stop iterative computation, which means the value of \( \lambda(n) \) can not be infinitely close to 0 or 1. Therefore, the value of auxiliary parameters should be limited to \( \epsilon(n) \in [-\epsilon^-, \epsilon^+] \), where the \( \epsilon^+ = 4 \) commonly[20-22]. So the range of joint parameters is \( [1 - \lambda^-, \lambda^+] \), where \( \lambda^+ = \text{sgm}(\epsilon^+) \).
2.2. Improved FLOM-CMA

Based on the traditional CMA, the fractional lower order statistics are introduced into the cost function. So the cost function of FLOM-CMA is [13]:

\[
J_p(w) = E\left\{ |y(n)|^p - R^q \right\}
\]  
\[(6)\]

Where \( |\cdot|^p \) and \( |\cdot|^q \) is the FLOMs; and the constant modulus \( R = E|s(n)|^{2p}/E|s(n)|^p \). Similar to CMA, owing to the constant modulus \( R \), the phase rotation of signal cannot be corrected here. To solve this problem, we improve the cost function as:

\[
J_p(w) = \frac{1}{2} E\left\{ |y_{i,R}(n)|^p - R_{R}^q \right\} \\
+ \frac{1}{2} E\left\{ |y_{i,I}(n)|^p - R_{I}^q \right\}
\]
\[(7)\]

In Eq.10, \( y_{i,R}(n) \) and \( y_{i,I}(n) \) represent the real and virtual parts of \( y_i(n) \), respectively. In order to make full use of the amplitude and phase information of constellation, the FLOM of modulus of real and imaginary parts are

\[
R_R = \frac{E|s_R(n)|^{2p}}{E|s_R(n)|^p}, \quad R_I = \frac{E|s_I(n)|^{2p}}{E|s_I(n)|^p}
\]

respectively. According to the definition in Eq.4., \( p \), \( q \) and \( pq \) must be valued in the range of \((0, \alpha)\). Therefore, the iterative relation of the weight vector can be expressed as:

\[
w_i(n+1) = w_i(n) - \mu_1 \frac{\partial J_p(w)}{\partial w} \\
= w_i(n) - \mu_1 p c_i(n) r_i(n)
\]
\[(8)\]

Where the \( \mu_1 \) is step-size of improved FLOM-CMA. Commonly, \( q = 2 \) and \( p < \alpha/2 \) are used in our paper and the equalizer error \( c_i \) is defined here.

\[
c_i = \left( |y_{i,R}(n)|^p - R_R \right)y_{i,R}(n) y_{i,R}(n)^{p-2} \\
+ j \left( |y_{i,I}(n)|^p - R_I \right)y_{i,I}(n) y_{i,I}(n)^{p-2}
\]
\[(9)\]

3. Simulation Result

In this paper, we have discussed the blind equalization algorithm in impulse noise environment. A concurrent adaptive switching blind equalization system is proposed here, and in this section, some simulation scenarios are used to compare the algorithm in this paper with the original FLOM-CMA, improved FLOM-CMA and the algorithm of [18]. The principle of FLOM-CMA[13] is similar to CMA, but the fractional lower order moments are used instead of the second order moments to suppress impulse noise. The improved FLOM-CMA in this paper is based on (11) and (12), which is dividing the complex signals into real and imaginary parts. Thus, the amplitude and phase information of signals are fully utilized. The algorithm of [18] is also a dual mode algorithm based on FLOM-CMA and DD-LMP. But the switching way is a ‘Stop-and-Go’ mode which is judged by whether the current output point of the decision is the same as the previous output of the decision. When they are not equal, the weight vector of DD-LMP is updated. It is also a kind of soft switching algorithm which is commonly used in the blind equalization of Gauss noise[28][29].

In our simulation scenarios, different transmitted signal, noise environments and channels are considered, but some of the parameters are fixed here. The length of simulation data \( N = 10^4 \); the initial
values of joint parameter is \( \lambda(l) = 0.5 \), \( \varepsilon(l) = 0 \); the length of each equalizers are assumed to be \( M = 9 \) and initialized with center tap, which is \( w_1(l) = w_5(l) = [0, 0, 0.01, 0, 0.01, 0] \). And the definition of generalized signal-to-noise ratio (GSNR) is

\[
\text{GSNR} = 10\log\left(\frac{E_r}{\gamma}\right),
\]

where \( E_r \) is the mean power of received signal and \( \gamma \) is the scale parameter of \( \text{S}_\alpha \text{S} \) noise. In order to compare the performance of each blind equalization algorithms, two criteria are used here. First, the inter symbol interference (ISI) is defined by

\[
\text{ISI}(n) = 10 \log \left( \frac{\sum_{n=1}^{N-M+1} |C_n|^2 - \left|C_n^\ast\right|^2_{\max}}{\left|C_n^\ast\right|^2_{\max}} \right)
\]

where \( C_n = h(n) \otimes w(n) \) is the convolution of channel impulse response and weight vector of blind equalizers. Second, \( \text{MSE}(n) = E\left[|s(n-\Delta) - y(n)|^2\right] \) is considered to evaluate the performance of algorithms.

And all the fractional lower order moments in our simulations are set to be \( p = 0.8 \).

Scenario I

In this scenario, 16QAM signal is used to compare the different algorithms. The impulse noise is \( \text{S}_\alpha \text{S} \) noise which \( \alpha = 1.8 \) and GSNR=30dB. A commonly channel is adopted which impulse responses is:

\[
h_1 = [-0.005 - 0.004j, 0.009 - 0.3j, -0.0024 - 0.104j, 0.864 + 0.52j, -0.218 + 0.273j, 0.049 - 0.074j, 0.016 + 0.2j]
\]

The iterative step of each equalizers are chosen to ensure the performance of equalization algorithms are good. So the iterative step of FLOM-CMA and improved FLOM-CMA are \( \mu = 10^{-3} \); the two iterative steps of the algorithm of [18] and our algorithm is \( \mu_1 = 10^{-3} \), \( \mu_2 = 1.5 \times 10^{-4} \); the iterative step of joint parameter is \( \mu_e = 100 \) [21].

As we can see in Fig. 3, in steady-state, compared with original FLOM-CMA, the improved FLOM-CMA have effectively used the amplitude and phase information of received signal so that the phase rotation is corrected, but both of their constellation are not well converged. Fig. 3(c) is output of the algorithm of [18], by combining the advantages of DD-LMP, the astringency of the constellation is obviously improved. However, because the DD-LMP algorithm can not be effectively equalization when the signal eye diagram is not opened, and the ‘Stop-and-Go’ mode will introduce a certain error jitter. To avoid the disadvantages of the above algorithms, the concurrent adaptive switching blind equalization in our paper makes a convex combination of two algorithms of improved FLOM-CMA and DD-LMP, the result of Fig. 3(d) shows that the convergence of this algorithm is better than other algorithms.

In order to avoid the accident caused by single experiment, scenario II analyzed the performances of each algorithms under different \( \text{S}_\alpha \text{S} \) noise conditions and different GSNR by 100 Monte Carlo experiments. The ISI and MSE curves are used to investigate the convergence speed and steady-state accuracy of the algorithms.
Fig.1. Constellation of each equalizers output: (a) FLOM-CMA (b) improved FLOM-CMA (c) the algorithm of [18] (d) the proposed algorithm
Performance comparison of each algorithm when $\alpha = 1.8$ and GSNR=30: (a) ISI curves; (b) MSE curves

Fig.2 Performance comparison of each algorithm when $\alpha = 1.8$ and GSNR=20: (a) ISI curves; (b) MSE curves

Firstly, we set $\alpha = 1.8$ and simulate the noise environment of GSNR=25dB and GSNR=30dB respectively. Other conditions are not changed here.

Fig. 4 compares the ISI and MSE curves of several blind equalization algorithms. Take the ISI curve as an example, in steady-state, the ISI of FLOM-CMA is nearly 18dB and improved FLOM-CMA is 20dB, both are converged at about 1600 points. By combining the DD-LMP, the algorithm of [18] have reduced the ISI of blind equalization system. But owing to the ‘stop-and-go’ mode, the advantages is not fully exploited here. On this basis, it is clearly that our convex combination algorithm fully combines the advantages of FLOM-CMA and DD-LMP. In the first 1700 points, the ISI curve of our system is close to improved FLOM-CMA which means joint parameter is nearly to 1. After rough convergence, our system soft-switch to DD mode and the ISI is reduced to about 34dB. The results also verify the previous analysis in this paper.

When GSNR=25dB, the influence of noise becomes larger, and the performance of several algorithms have declined. The MSE curves show that the lower GSNR has introduced more pulse peak. After 100 independent repeated experiments, the average MSE curve seems to have more mutation values, but actually the algorithm has been converged.

Secondly, we fix the value of GSNR=30dB and compare the performance of our system at different $\alpha$ and Fig. 6 is $\alpha = 1.5$. Compared Fig. 4(a) and Fig. 6(a), we can find that under different $\alpha$ values, when the algorithm converges, the minimum value of ISI remains unchanged. However, the smaller the $\alpha$ value, the greater the amplitude of the pulse in the noise, and the mutation point will appear when convergence occurs. The MSE curves in Fig. 4(b) and Fig. 6(b) also prove this conclusion.
4. Conclusion
In this paper, the improved FLOM-CMA has been discussed, and then, a new concurrent blind equalization algorithm for impulse noise environment has been proposed, which is convex combining the improved FLOM-CMA and DD-LMP to suppress the impulse noise and achieve signal equalization. Our system can take full advantage of the fast convergence of FLOM-CMA and the high accuracy of DD-LMP in steady-state and realize adaptive switching in two modes by introducing the joint parameter, which has effectively avoided the error caused by hard-switching. In addition, we also analysed the combined EMSE of the system under non-stationary conditions. The simulation results show that, compared with the traditional blind equalization algorithms, the proposed blind equalization algorithm can effectively improve the convergence precision of the equilibrium on the premise of guaranteeing the convergence speed and more suit for different impulse noises.

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