

A Multi-modulus Blind Equalization Algorithm Based on Memetic Algorithm

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Abstract. In view of slow convergence speed, large steady mean square error (MSE), and existing blind phase for the constant modulus blind equalization algorithm(CMA), a multi-modulus blind equalization algorithm based on memetic algorithm(MA-MMA) is proposed, which combines the basic idea of intelligent optimization algorithm and introduces the individual own evolution and social behavior among individuals to the blind equalization technology. In this proposed algorithm, the reciprocal of the cost function of multi-modulus blind equalization algorithm(MMA) is defined as the fitness function of the memetic algorithm(MA), the initial optimal weight vector of the MMA is optimized by using the global information sharing mechanism and local depth search ability of the MA. When the initial optimum weight vector of the MMA is obtained, the weight vector of the MMA may be updated. The simulation results with the higher-order APSK multi-modulus signals show that, compared with the CMA, the MMA, and the multi-modulus blind equalization algorithm based on genetic algorithm(GA-MMA), the proposed MA-MMA has the fastest convergence speed, smallest mean square error(MSE), and clearest output constellations.

Introduction

In a communication system, blind equalization algorithm is introduced to the receiver in order to effectively eliminate the inter-symbol interference(ISI) caused by limited bandwidth and multi-path propagation. In blind equalization algorithms, constant modulus blind equalization algorithm(CMA) can make the output constellation points distribute in the circle with radius R_c (statistical mode value of input signal) as far as possible, its cost function is only related to the received sequence amplitude, so CMA is very suitable to equalize constant modulus signals[1]. However, the different modulus constellation points of high order QAM or APSK signals are distributed in different radius of the circle. If CMA is used to equalize high order QAM or APSK signals, the output constellation points of high order QAM or APSK signals will be focused single circle, there will be large mean square error(MSE), and CMA even will become invalid. In recent years, some multi-modulus blind equalization algorithms(MMAs) were proposed to equalize multi-modulus signals. The MMAs can make the output constellation points of high order QAM or APSK signals equalize to different circles with different radii[2][3]. Compared with CMA, especially for non-square constellation and intensive constellation, MMA can make full use of the statistical characteristics of symbols. However, the MMA and CMA all exist the model error so that the convergence speed and residual MSE aren't still very ideal.

Memetic Algorithm is an optimization algorithm with genetic mechanism and local searching, can make all individuals obtain local optimal value after iteration, and is easy to understand and implement, as well as has simple operation [4][5].

According to characteristics of the MA and the MMA, a multi-modulus blind equalization algorithm based on MA is proposed. It can search global optimal group fast by MA, which is used

as the initial optimal weight vector of the MA. The simulation results show that, the proposed algorithm has the ability to equalize higher-order multi-modulus signals, its convergence speed is faster and its steady MSE is smaller.

Multi-modulus Blind Equalization Algorithm

The MMA is shown in Figure 1. In Fig.1, a decision device is used to determine the decision modulus value R_D of multi-modulus signals. $\mathbf{x}(n)$ is the receiving sequence to equalizer, $\mathbf{w}_D(n)$ is the weight vector of the equalizer, $z(n)$ is the output of the equalizer, $\hat{z}(n)$ is estimated signal of $z(n)$, $e_D(n)$ is error signal, R_J is sampling modulus value. After $z(n)$ passes nonlinear estimator without memory, the estimated sequence $\hat{z}(n)$ instead of the expected signal can be obtained. The memory less nonlinear function of the MMA is defined as

$$\hat{z}(n) = g[z(n)] = z(n)[1 + R_D^2 - |z(n)|^2] \quad (1)$$

R_J is defined as

$$R_J = \frac{E[|z(n)|^4]}{E[|z(n)|^2]} \quad (2)$$

The output of the MMA is given by

$$z(n) = \mathbf{w}^T(n)\mathbf{x}(n) \quad (3)$$

The error signal is defined as

$$e_D(n) = \hat{z}(n) - z(n) = z(n)[R_D^2 - |z(n)|^2] \quad (4)$$

The cost function of the MMA is written as

$$J_{MMA}(n) = E\{[R_D^2 - |z(n)|^2]^2\} \quad (5)$$

The weight vector iterative formula of the MMA is obtained by stochastic gradient and written as

$$\mathbf{w}_D(n+1) = \mathbf{w}_D(n) - \mu_D e_D(n) \mathbf{x}^*(n) \quad (6)$$

where μ_D is step size factor.

According to decision modulus value R_D , MMA can adjust error function. For 32-APSK signal, its constellations can be known as the star QAM[6][7] and shown in Figure 2. In Figure2, the input constellation points are distributed in three different circles with different radii, two circles with the dashed border are decision boundary condition for decision device. The constellations are divided into three regions correspond to three error function by two decision circles.

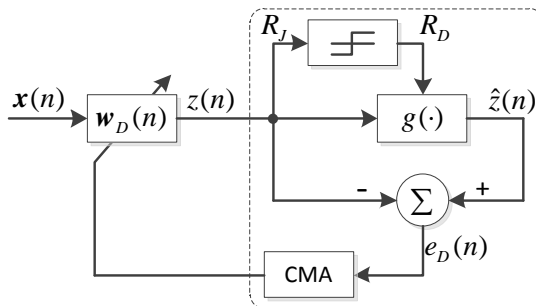


Fig. 1 MMA

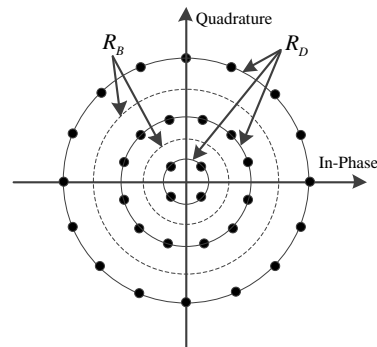


Fig. 2 32-APSK

In the constellation, the radius R_D of circle are ranked as R_{D1} , R_{D2} , and R_{D3} in ascending order. The radius of decision circle in ascending order are R_s , R_b .

The equalizer output $z(n)$ is input to decision device. In order to obtain R_D and $e_D(k)$, it is necessary to compare R_J with the decision boundary R_s and R_b . So we have

$$R_D = \begin{cases} R_{D1}, R_J < R_s \\ R_{D2}, R_s < R_J < R_b \\ R_{D3}, R_J > R_b \end{cases} \quad (8)$$

The error function of 32-APSK is given as

$$e_D(n) = \begin{cases} z(n)[R_{D1}^2 - |z(n)|^2], R_J < R_s \\ z(n)[R_{D2}^2 - |z(n)|^2], R_s < R_J < R_b \\ z(n)[R_{D3}^2 - |z(n)|^2], R_J > R_b \end{cases} \quad (9)$$

For different modulation modulus, the decision rules aren't the same. The equalization performance of the MMA mainly depends on the selection of decision condition R_s and R_b . MMA has some advantages such as low computational complexity and the fast convergence speed, but its residual MSE is large and its convergence speed is slow.

Correlation Algorithms

Genetic algorithm. Genetic algorithm is a non deterministic quasi natural algorithm, which is a simulation of biological genetic and evolutionary process[8]. It starts from a population representative of a potential solution of possible problem, a new generation of population can be generated by genetic operator of nature genetics such as code, population initialization, and fitness calculation, as well as the hybrid and mutation. The whole process simulates the process of biological evolution in natural, the environmental adaptability of the newborn generation is stronger than that of previous generation. The decoded best individual in the last generation can be served as the approximate optimal solution of the problem.

Memetic algorithm. The word ‘‘Memetic’’ is derived from ‘meme’, which is generally understood as ‘cultural gene’. Therefore, Memetic algorithm is called as a culture genetic algorithm, which simulates the development of human civilization. Its operation process is similar to the genetic algorithm, but its local search can make all individuals in each time of iteration reach the local optimal. The MA usually can be defined as the combined algorithm of evolution and personal learning in a much more diverse background [9]. The following piece of pseudo-code can make things more explicit.

Begin

$t := 0;$

$X(t) := \text{InitialPop}();$

while(*stopping criteria not met*) **do**

$X'(t) := \text{Recombine}(X(t));$

$X'(t) := \text{Mutate}(X(t));$

$X'(t) := \text{Select}(X'(t));$

$\text{EvaluateFitness}(X'(t));$

$X(t+1) := \text{SelectNewPop}(X(t), X'(t));$

$X'(t+1) := \text{LocalSearch}(X(t+1));$

$t := t+1;$

end

end

Step1: *Code*. Binary code is used.

Step2: *Initialization of the population*. The initial population is generated randomly (where N is the population size) and denoted as $X = [X_1, X_2, \dots, X_N]$.

Step3: *Recombination*. In accordance with the recombination probability (P_c), two individuals have been selected randomly to generate two new individuals of new generation of population.

$$X'_1 = \omega_1 X_1 + (1 - \omega_1) X_2$$

$$X'_2 = \omega_2 X_2 + (1 - \omega_2) X_1$$

(10)

where X_1 and X_2 are randomly selected as two parent individuals, X'_1 and X'_2 are the corresponding new offspring individuals after recombination calculation, ω_1 and ω_2 are two random number in $[0,1]$.

Step 4: *Mutation operator*. After calculating according to certain rules, some individuals with mutation probability (P_m) in new generation of population are selected. The mutate operation is given by

$$X' = \begin{cases} X + (X_{\max} - X)(rand \times g_t)^2, & sign = 0 \\ X - (X - X_{\min})(rand \times g_t)^2, & sign = 1 \end{cases}$$

(11)

where $g_t = t / G$ is the identification of the population evolution (where t is the current evolution times, G is the maximum of evolution times). X is the selected mutation individuals, X' is mutated individuals, $rand$ is a random number in $[0,1]$, $sign$ is set 0 or 1, X_{\max} and X_{\min} are the upper and lower limits of the parameters, respectively.

Step 5: *Evaluate fitness*. Evaluate fitness is denoted as $fitness(X)$.

Step 6: *Select operator*. N excellent individuals (high fitness value) in the current population are selected to make them enter next iteration and some individuals with low fitness value will be eliminated. Each probability (P_i) of individual is defined as

$$P_i = \frac{fitness(X_i)}{\sum fitness(X_i)}, \quad i = 1, 2, \dots, N$$

(12)

where $fitness(X_i)$ is the i th individual fitness value.

Step 7: *local search*. The local search of all individuals is carried out by using the MATLAB built-in optimization function.

Step 8: *Iteration end*. When the current iteration number is greater than the maximum iteration time, the optimal solution is output, otherwise go to step 3.

Based on the mechanism of metaphor in the theory of cultural development, the MA is a collection of global search and heuristics local search, it is different from other intelligent optimization algorithms with specific mathematical model, and it is more of a thought or frame.

Multi-Modulus Blind Equalization Algorithm Based on MA

When the MA is introduced to the MMA, multi-modulus blind equalization algorithm based on MA(MA-MMA) is proposed and shown in Fig.3. In Fig.3, $s(n)$ is the transmitted signal, $n_0(n)$ is Gaussian white noise.

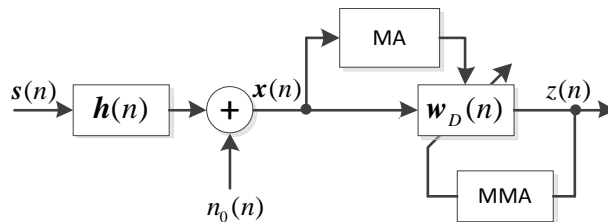


Fig.3 MA-MMA

Assume that the initial population of randomly generation is $X = [X_1, X_2, \dots, X_N]$, each individual X_i corresponds to one of the weight vector of the MMA. The optimal weight vector of the MMA can be obtained by local search and global evolution. In the MA-MMA, the reciprocal of

cost function of MMA is defined as the fitness function of the MA, i.e.

$$fitness(X_i) = \frac{1}{J_{MMA}(X_i)} \quad i = 1, 2, \dots, N \quad (14)$$

Simulation and Analyses

In order to verify the performance of the MA-MMA, the simulation test of the MA-MMA was carried out and compared with the CMA, MMA, and GA-MMA. In the test, $N = 50$, $S = 20$, $G = 50$, $P_c = 0.7$, and $\mathbf{h} = [0.9656 \ -0.0906 \ 0.0578 \ 0.2368]$, the received signal-to-noise ratio $SNR = 30\text{dB}$, the equalizer had 11 order transversal tap structure, the center tap coefficient of the CMA and MMA were set to 1, the other tap coefficient were set to 0, maximum iterations of all simulation $iter = 10000$, Monte Carlo times $M = 2000$. The step-sizes of the CMA and MMA were 1×10^{-5} , the step-sizes of the MA-MMA and GA-MMA were 5×10^{-6} , the simulation results were shown in Figure 4.

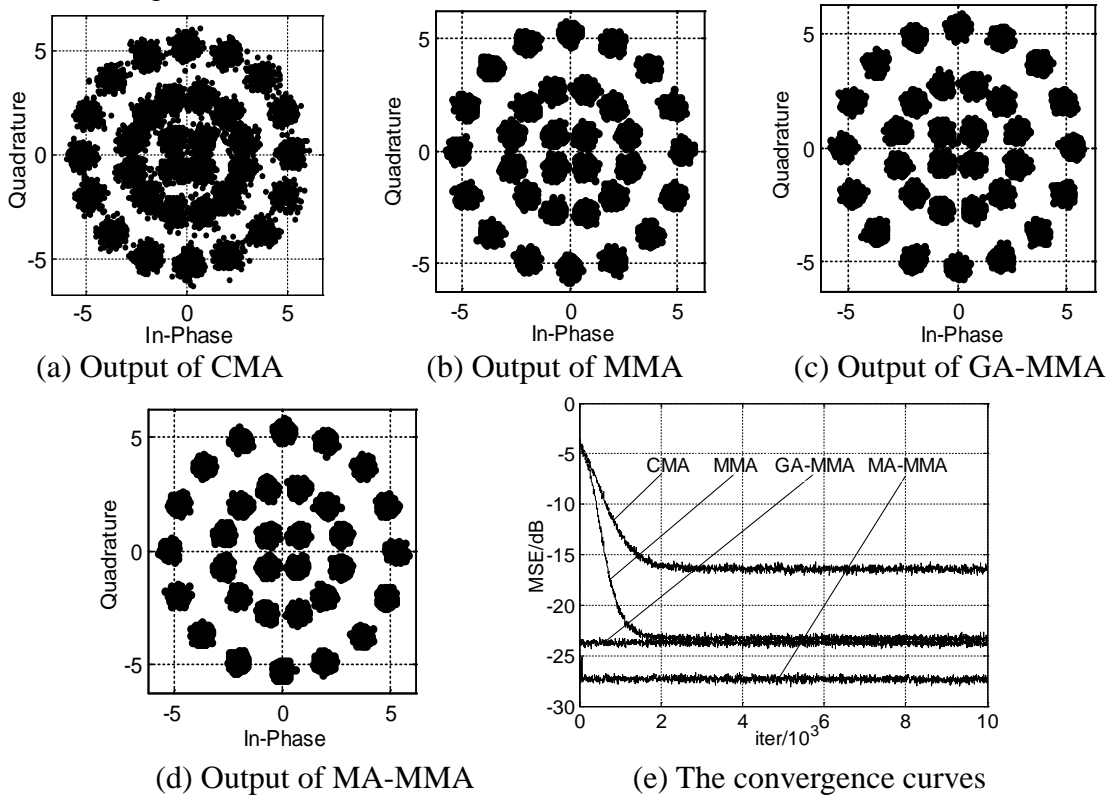


Fig. 4 Simulation results of 32-APSK

In the same SNR, the iterations and the steady MSE were shown in Table 1.

Tab. 1 Convergence iterations and steady MSE

Algorithms	MSE/dB	Iterations
CMA	-17	2200
MMA	-23	1800
GA-MMA	-24	100
MA-MMA	-27	100

From Figure 4 and Table 1, we can come some following conclusions: (1) the equalization performance of the MA-MMA and the GA-MMA are much better than that of the MMA, the convergence speed of the MA-MMA is slightly faster than that of the GA-MMA, but its MSE is smallest. (2) the output constellations of the MA-MMA is more clearer and more compact than those of the CMA and MMA. Therefore, for higher-order multi-modulus signals, the MA-MMA

outperforms the CMA, MMA, and GA-MMA in improving convergence speed and reducing steady MSE.

Conclusions

This paper proposes a multi-modulus blind equalization algorithm based on Memetic Algorithm. This proposed algorithm makes full use of the genetic mechanism and local searching of the MA to obtain the initial optimal weight vector, so that the equalization performance of the MMA can be improved. The simulation results show that, for higher-order multi-modulus 32-APSK signals, MA-MMA has faster convergence speed and smaller steady MSE comparison with traditional CMA, MMA, and GA-MMA.

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