Orthogonal Wavelet Transform Dynamic Weighted Multi-Modulus Blind Equalization Algorithm Based on Dynamic Particle Swarm

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Abstract— For improving the equalization performance of higher-order QAM signals, orthogonal Wavelet transform dynamic Weighted Multi-Modulus blind equalization Algorithm based on the Dynamic Particle Swarm Optimization(DPSO-WWMMA) is proposed. In this proposed algorithm, dynamic particle swarm optimization algorithm and orthogonal wavelet transform are introduced into dynamic Weighted Multi-Modulus blind equalization Algorithm(WMMA). Accordingly, the equalizer weight vector can be optimized by Dynamic Particle Swarm Optimization(DPSO) algorithm, the autocorrelation of the input signals can be reduced via using orthogonal wavelet transform, and the WMMA is used to choose appropriate error model to match QAM constellations. The theoretical analyses and computer simulations in underwater acoustic channels indicate that the proposed algorithm can obtain the fastest convergence rate and the smallest steady mean square error in equalizing high-order QAM signals. So, the proposed algorithm has important reference value in the underwater acoustic communications.

Index Terms—dynamic particle swarm, orthogonal wavelet transform, weighted multi-modulus blind equalization algorithm, underwater acoustic communication

I. INTORDUCTOIN

In underwater acoustic communication system, in order to eliminate the inter-symbol interference(ISI) caused by the limited bandwidth and multipath propagation of the underwater acoustic channel, blind equalization technique is introduced to the receiving end. Compared with the traditional adaptive equalization algorithm, the blind equalization technique doesn't need to transmit periodic training sequence, the channel change only is compensated by the statistical properties of the receiving signals, and channel equalization is realized, as well as higher-order QAM modulation signals become the important means of modern communication modulation with its high frequency band utilization rate. The complexity of the QAM signals is greatly improved with the modulation order number increases, it is difficult to equalize the higher-order QAM modulation signals. Therefore, the higher-order QAM modulation technology has already caused the wide attention.

In the blind equalization algorithms, the traditional constant modulus blind equalization algorithm can well equalize constant modulus signals, when the higher-order non-constant modulus QAM signals are equalized, the input constellation diagram distributed in several different radius circles is output to the same circle, the great mean square error are caused, the communication quality is seriously affected. In the multi-modulus blind equalization algorithms [3][4] [5], the equalizer outputs are divided into real and imaginary parts, the respective modulus of in-phase component and quadrature component are selected. The great mean square error caused by the single decision circle of the CMA can be reduced by this method and the channel can be equalized

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effectively. The thought of the dynamic weighted multimodulus algorithm is to make full use of the prior information of constellation diagram, the appropriate error model is selected to match the constellation diagram of the transmitted QAM signals in order to reduce the steady-state mean square error further, and the input signal's autocorrelation is reduced via introducing the orthogonal wavelet transform [8][9], as well as the convergence rate is accelerated. The equalizer weighted vector of the MMA and CMA are updated by using the gradient descent algorithm and it is easy to fall into local convergence, so it is difficult to obtain the global optimal solution. The dynamic particle swarm optimization (DPSO) algorithm is a global stochastic searching optimization algorithm[10][11][12][13][14], it has good ability to track dynamic extreme value and is able to detect the changes of the external environment, the change of the external environment is provided by the cumulative difference of the sensitivity particle fitness value in two adjacent iteration. Accordingly, the possibility of the population falling into local minimum can be avoided. Based on the above analyses, in this paper, the orthogonal wavelet transform theory, dynamic weighted multi- modulus blind equalization algorithm and DPSO algorithm are combined, an orthogonal wavelet transform dynamic weighted multi-modulus blind equalization algorithm based on the optimization of dynamic particle swarm is proposed. Compared with orthogonal dynamic weighted multi-modulus blind equalization algorithm, the orthogonal dynamic weighted multi-modulus blind equalization algorithm based on DPSO algorithm has fastest convergence speed and least mean square error.

The organization of the lecture is as follows. After a general introduction of the current situation of the MMA, CMA, and DPSO algorithm, orthogonal dynamic weighted multi-modulus blind equalization algorithm has been discussed in section II. Dynamic particle swarm wavelet dynamic weighted multi modulus algorithm based on DPSO algorithm is proposed in section III. In section IV, The analyses and simulation results of the proposed algorithm has been discussed. The lecture has been concluded in section V.

II. ORTHOGONAL DYNAMIC WEIGHTED MULTI-MODULUS BLIND EQUALIZATION ALGORITHM

After the orthogonal wavelet transform is introduced into dynamic weighted multi-modulus blind equalization algorithm(WMMA), we can get the orthogonal dynamic weighted multi-modulus blind equalization algorithm (WWMMA), and its principle diagram is shown as Fig.1. In this algorithm, the real and imaginary parts of the input signals of the equalizer are transformed by orthogonal wavelet transform, respectively, and their energies are normalized, the autocorrelation of the input complex signals can be reduced, so an equalizer with good equalization performance could be designed.



Figure 1. Orthogonal wavelet transform dynamic weighted multi-modulus blind equalization algorithm

In Fig.1, a(k) is a transmitted complex signal source, c(k) is the channel impulse response with length M, w(k) is additive white Gaussian noise, y(k) is the complex input signals of the equalizer, and R(k) is the result after transforming y(k) via using orthogonal wavelet, and $y(k) = [y(k+L), L, y(k), L, y(k-L)]^T$, f(k) is the equalizer weighted coefficient, and $f(k) = [f_0(k), L, f_L(k)]^T$. z(k) and $\hat{z}(k)$ are the output complex signal of the equalizer and decision device.

The input signal of equalizer y(k) may be expressed as

$$y(k) = \sum_{m=0}^{M-1} c(m)a(k-m) + w(k).$$
 (1)

From the theory of wavelet analyses, when the equalizer weight vector f(k) is a finite impulse response, it can be expressed as a group of orthogonal wavelet basis function, i,e.,

$$f(k) = f_r(k) + jf_i(k)$$
. (2)

$$\begin{cases} f_r(k) = \sum_{j=1}^{J} \sum_{m=0}^{k_j} d_{r_{j,m}}(k) \cdot \varphi_{j,m}(k) + \sum_{m=0}^{k_j} v_{r_{J,m}}(k) \cdot \phi_{J,m}(k) \\ f_i(k) = \sum_{j=1}^{J} \sum_{m=0}^{k_j} d_{i_{j,m}}(k) \cdot \varphi_{j,m}(k) + \sum_{m=0}^{k_j} v_{i_{J,m}}(k) \cdot \phi_{J,m}(k) \end{cases}$$
(3)

where k denotes the length of the equalizer and k = 0,1,L, $L-1,L = 2^{J}$. J is the largest scale of wavelet decomposition, k_{j} is the maximum translation scale wavelet function and $k_{j} = L/2^{j} - 1(j = 1,2,L,J)$. $\varphi_{j,m}(k)$ and $\varphi_{J,m}(k)$ denote the wavelet function and the scaling function, respectively. $d_{rj,m}(k)$ and $v_{rJ,m}(k)$ are the real part of the equalizer coefficient, $d_{rj,m}(k) = \langle f_{r}(k), \varphi_{j,m}(k) \rangle$, and $v_{rJ,m}(k) = \langle f_{r}(k), \varphi_{J,m}(k) \rangle$, and $v_{iJ,m}(k) = \langle f_{i}(k), \varphi_{j,m}(k) \rangle$. According to wavelet transform theory, the equalizer input signal $\mathbf{R}(k)$ can be expressed as

$$\boldsymbol{R}(k) = \boldsymbol{R}_r(k) + j\boldsymbol{R}_i(k) = \boldsymbol{Q}\boldsymbol{y}_r(k) + j(\boldsymbol{Q}\boldsymbol{y}_i(k)). \quad (4)$$

where $\mathbf{R}_r(k)$ and $\mathbf{R}_i(k)$ are the real and imaginary part of the input signal $\mathbf{R}(k)$, respectively, and they can be written as

$$\boldsymbol{R}_{r}(k) = [u_{r1,0}(k), u_{r1,1}(k), L, u_{rJ,k_{J}}(k), s_{rJ,0}(k), L, s_{rJ,k_{J}}(k)]^{T}.$$
(5)

$$\begin{cases} u_{rj,m}(k) = \sum_{l=0}^{L-1} y_r(k-l)\varphi_{j,m}(l) \\ s_{rJ,m}(k) = \sum_{l=0}^{L-1} y_r(k-l)\phi_{J,m}(l) \end{cases}$$
(6)

$$\boldsymbol{R}_{i}(k) = [u_{i1,0}(k), u_{i1,1}(k), L, u_{iJ,k_{J}}(k), s_{iJ,0}(k), L, s_{iJ,k_{J}}(k)]^{T}.$$
(7)

$$\begin{cases} u_{ij,m}(k) = \sum_{l=0}^{L-1} y_i(k-l)\varphi_{j,m}(l) \\ s_{iJ,m}(k) = \sum_{l=0}^{L-1} y_i(k-l)\phi_{J,m}(l) \end{cases}$$
(8)

where $u_{ij,m}(k)$ and $s_{rJ,m}(k)$ denote the real part of the wavelet and scale transform coefficients, respectively. $u_{ij,m}(k)$ and $s_{iJ,m}(k)$ denote the imaginary part of the wavelet and scale transform coefficients, respectively.

The equalizer output is given by

$$z(k) = z_r(k) + jz_i(k) = \boldsymbol{f}_r^T(k)\boldsymbol{R}_r(k) + j\boldsymbol{f}_i^T(k)\boldsymbol{R}_i(k).$$
(9)

where $f_r^T(k)$ and $f_i^T(k)$ (superscript T denotes transpose operation) are the equalizer weighted vector of the real and the imaginary part of the vector, respectively. $z_r(k)$ and $z_i(k)$ are the real and imaginary parts of the equalizer output signals, respectively. The cost function of weighted multi-modulus blind equalization algorithm is defined as

$$J_{WMMA} = E\{(z_r^2(k) - |\hat{z}_r(k)|^{\lambda(k)} R_{rWMMA}^2)^2.$$
(10)

where

$$R_{rWMMA}^{2} = E(a_{r}^{4}(k))/E(|a_{r}(k)|^{2+\lambda(k)}), \qquad (11a)$$

$$R_{iWMMA}^{2} = E(a_{i}^{4}(k))/E(|a_{i}(k)|^{2+\lambda(k)}) .$$
(11b)

where $\hat{z}_r(k)$ and $\hat{z}_i(k)$ are the real and imaginary part of the decision signal $\hat{z}(k)$. $\lambda(k)$ is the weighted factor, which determines the convergence speed and steady-state mean square error of the algorithm. The iterative formula of the mean square error (MSE) is given by

$$MSE(k+1) = \alpha MSE(k) + (1-\alpha) |z(k) - \hat{z}(k)|^{2}.$$
 (12)

$$\begin{cases} e_{r,WMMA}(k) = z_r(k)(z_r^2(k) - |\hat{z}_r(k)|^{\lambda(k)} R_{rWMMA}^2) \\ e_{i,WMMA}(k) = z_i(k)(z_i^2(k) - |\hat{z}_i(k)|^{\lambda(k)} R_{iWMMA}^2) \end{cases}$$
(13)

From Eq.(13), we can know that the value of $\lambda(k)$ is affected by the MSE directly. The eye pattern of signals are completely closed in the initial stage of equalization process, $\lambda(k)$ should take a smaller value so that the error curves can achieve global convergence. When the eye pattern become more and more clearer, the value of $\lambda(k)$ must be improved to reduce the MSE. In order to match the actual signals and to reduce the steady-state mean square error, it is necessary to design the more accurate error model. According the literature[7], the weighted value $\lambda(k)$ can be written as

$$\lambda(k) = \begin{cases} 0 & MSE(k) > d/2 \\ 1 - MSE(k) & d/2 \ge MSE(k) > 2d/5 \\ 1.2 - MSE(k) & 2d/5 \ge MSE(k) > 3d/10 \\ 1.5 - MSE(k) & 3d/10 \ge MSE(k) > d/10 \\ 1.8 - MSE(k) & d/5 \ge MSE(k) > d/10 \\ 2 & d/10 \ge MSE(k) \end{cases} . (14)$$

where the d is the minimum distance among the constellation points(i.e., the minimum Euclidean distance). According to the literature [15], we can know that the parameter d denotes the ability of QAM signals to resist the Gaussian white noise. The energy mean and peak of the constellations without energy normalized QAM signals are expressed as

$$E = \sum_{i=1}^{M} (a_i + b_i) / M .$$
 (15)

$$P = \max(a_i + b_i). \tag{16}$$

where a_i and b_i denote the constellation points of QAM signals, *M* is the number of constellation points in any quadrant. The peak to average ratio is written as $\gamma = P/E$. After the constellation energy normalization, we can get the minimum distance *d* among the adjacent constellation points and $d = 2/\sqrt{E}$.

The iterative formula of the equalizer weighted vector can be written as

$$\begin{cases} \boldsymbol{f}_{r}(k+1) = \boldsymbol{f}_{r}(k) - \mu \hat{\boldsymbol{R}}_{r}^{-1}(k) \boldsymbol{e}_{r.WMMA}(k) \boldsymbol{R}_{r}^{*}(k) \\ \boldsymbol{f}_{i}(k+1) = \boldsymbol{f}_{i}(k) - \mu \hat{\boldsymbol{R}}_{i}^{-1}(k) \boldsymbol{e}_{i.WMMA}(k) \boldsymbol{R}_{i}^{*}(k) \end{cases}$$
(17)

where $\hat{\mathbf{R}}_{r}^{-1}(k) = \text{diag}[\sigma_{ij,0}^{2}(k), \sigma_{ij,1}^{2}(k), \mathcal{L}, \sigma_{rI,k_{J}-1}^{2}(k), \sigma_{rJ+1,0}^{2}(k)]$, $\mathcal{L}, \sigma_{iJ+1,k_{J}-1}^{2}(k)]$, $\sigma_{ij,k}^{2}(k)$ and $\sigma_{rJ+1,k_{J}}^{2}(k)$ denote the average power estimation of the real part of the wavelet coefficients $u_{ij,m}(k)$ and the scale transform coefficients $s_{rJ,m}(k)$. $\sigma_{ij,k}^{2}(k)$ and $\sigma_{iJ+1,k_{J}}^{2}(k)$ denote the average power estimation of the imaginary part of the wavelet coefficients $u_{ij,m}(k)$ and scale transform coefficients $s_{iJ,m}(k)$, and

$$\begin{cases} \hat{\sigma}_{rj,m}^{2}(k+1) = \beta \hat{\sigma}_{rj,m}^{2}(k) + (1-\beta) | u_{rj,m}(k) |^{2} \\ \hat{\sigma}_{rJ+1,m}^{2}(k+1) = \beta \hat{\sigma}_{rJ+1,m}^{2}(k) + (1-\beta) | s_{rJ,m}(k) |^{2}. \end{cases}$$
(18)

$$\begin{cases} \hat{\sigma}_{ij,m}^{2}(k+1) = \beta \hat{\sigma}_{ij,m}^{2}(k) + (1-\beta) |u_{ij,m}(k)|^{2} \\ \hat{\sigma}_{iJ+1,m}^{2}(k+1) = \beta \hat{\sigma}_{iJ+1,m}^{2}(k) + (1-\beta) |s_{iJ,m}(k)|^{2} \end{cases}$$
(19)

where β is the smoothing factor and $0 < \beta < 1$. Up to now, orthogonal wavelet dynamic weighted multi-modulus blind equalization algorithm(WWMMA) is established.

III. DYNAMIC PARTICLE SWARM WAVELET DYNAMIC WEIGHTED MULTI MODULUS ALGORITHM

A. Basic Idea

The initialization position vector of a set of random particles(i.e., initialization weighted vector of equalizer) is used as the decision variables of the DPSO algorithm, the equalizer input signals are taken as the input signals of the DPSO algorithm. Based on the cost function of multi-modulus blind equalization algorithm, we can determine the fitness function of the DPSO algorithm and use the DPSO algorithm to find the optimal equalizer weighted vector (i.e., the optimal position vector of particle swarm). The weighted vector is regard as the initialization weighted multi-modulus blind equalization algorithm at this time. The inverse cost function of multi-modulus blind equalization algorithm is defined as the fitness function of QPSO algorithm, it is written as

$$F(f_i) = 1/J_{MMA}(f_i), i = 1, 2, L, M$$
. (20)

where $J_{MMA}(f_i) = E\{(z_r^2(k) - R_{rMMA}^2)^2 + (z_i^2(k) - R_{iMMA}^2)^2\}$ and it is called as the cost function of multi-modulus blind equalizer. $R_{rMMA}^2 = E(a_r^4(k))/E(|a_r(k)|^2)$ and $R_{iMMA}^2 = E(a_i^4(k))/E(|a_i(k)|^2)$. *M* is the number of particles, f_i is the position vector of particles corresponding to the individual of equalizer weighted vector.

B. Dynamic Particle Swarm Optimization Weighted Vector Algorithm

The position and speed searching model are used in the DPSO algorithm, each particle is corresponded to a candidate solution of the selected problem. The quality of solution is determined by the value of fitness function. The initialization position vector of the *i* th particle is written as $x_i = (x_{i1}, x_{i2}, L, x_{iD})$ and the velocity $v_i = (v_{i1}, v_{i2}, L, v_{iD})$. x_{id} and v_{id} represent the *d* th dimension of the position vector and the *d* th dimension of the position vector and the *d* th dimension of the initial particle swarm is *W* and $W = [W_1, W_2, L, W_m]$, it is corresponded to the equalizer weighted vector of the particle. The particles update their own speed and position according to the following expression[10].

$$v_{id}(t+1) = wv_{id}(t) + c_1 r_1(p_{id}(t) - x_{id}(t)) + c_2 r_2(p_{sd}(t) - x_{id}(t)).$$
(20)

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1).$$
 (21)

$$w = w_{\max} - ((w_{\max} - w_{\min}) / N)t .$$
 (22)

where i = 1, L, m, d = 1, L, D, D is the spatial dimension, t denotes the t th iteration, c_1 and c_2 are acceleration factors. r_1 and r_2 are random number within [0,1], N is the maximum number of iterations of the particle swarm algorithm. w is inertia weighted factor, w_{max} and w_{\min} represent the maximum and minimum inertia weighted factor, respectively. Particles dynamically trace the two extreme values to update the position and velocity vector in the optimization process. The current iteration times produce the optimal value, in other words, the individual optimum vector $p_i = (p_{i1}, p_{i2}, L, p_{iD})$ and p_{id} is the individual of the *d* th particle's dimension. The current global optimal vector of the entire particle swarm may be written as $p_g = (p_{g1}, p_{g2}, L, p_{gD})$ and p_{gd} is the global minimum of the particle's d th dimension. The fitness values of the remembered personal best position and global best position are changing with dynamic environment. Accordingly, it is difficult to effectively approach to the optimal position vector in a dynamic environment.

We can improve the particle swarm in two aspects: the first is the introduction of the detection mechanism, it can provide the ability to perceive the changes in the external environment. In the D dimensional space, there are n_1 particles and n_2 sensitive particles and $n_1 \neq n_2$. We must calculate the fitness value fit of the particles and the fitness value *fittest* of the sensitive particles, and accumulate the fitness values of the sensitive particle in each iteration. The individual optimal and global optimal position vector are got by the comparison method in the end. The difference between the fitness values of two adjacent sensitive particle is calculated, let $\Delta F =$ oFitness-nFitness, we use nFitness to denote the fitness value accumulation after the sensitive particle second initialization and oFitness to denote fitness value accumulation of the sensitive particle. If the value of ΔF isn't 0, the external environment will change. The second is the introduction of the response mechanism. When the environment changes, we use some response mechanism to update the population that reinitializes the particle's position and velocity vector to fit the dynamic environment. The above analyses can be described as the following program:

If abs(oFitness-nFitness) > 0, then

 $index = randperm(n_1); \ x(index(1:10),:) = rand(10, D);$ v(index(1:10),:) = rand(10, D);

Through the above descriptions, we can know that, if abs(oFitness-nFitness) > 0, the particle's position vector and velocity vector can be reinitialized at a certain level, the most optimal position vector of the population in the new particle swarm solution space can be re-found, so as to maintain the diversity of the population and to avoid fall into the premature convergence of the population. For the DPSO algorithm, we take the last particles optimal position vector as the equalizer optimal weighted vector, that is to say, the p_{gbest} always is treated as the initialization weighted vector of orthogonal wavelet dynamic weighted multi-modulus blind equalizer and $p_{gbest} = (p_{g1}, p_{g2}, L, p_{gD})$. Up to now, orthogonal Wavelet transform dynamic Weighted Multi-Modulus blind equalization Algorithm based on the Dynamic Particle Swarm Optimization(DPSO-WWMMA) is established.

IV. SIMULATION EXPERIMENT

In order to validate the validity of the DPSO-WWMMA, the simulation tests were carried out and compared with dynamic Weighted Multi-Modulus blind equalization Algorithm based on the Dynamic Particle Swarm Optimization(DPSO-WMMA) and dynamic Weighted Multi-Modulus blind equalization Algorithm (WMMA).

A. Simulation I

In the experiment, the underwater acoustic mixed phase channel C= [0.3132 -0.1040 0.8908 0.3134] [16], the transmitted signals were 64QAM, the length of the equalizer was 16, the SNR was 25dB. DB2 orthogonal wavelet was used to decompose the input signal and its level was 2. The initial value of the power was 10, the forgetting factor $\beta = 0.999$, MSE(1)=2, and the eighth tap coefficient of the WWMMA algorithm was set to 1, and the other was 0. The step-size $\mu_{\rm WMMA} = 3 \times 10^{-6}$, $\mu_{\rm DPSO-WMMA} = 2.5 \times 10^{-6}$, and $\mu_{\rm DPSO-WMMA} = 3 \times 10^{-6}$. The 100 times Monte-Carlo simulation results were shown in Fig.2.





Figure.2 Simulation results for channel

From the Fig.2, we can know that the convergent speed of the DPSO-WWMMA has an improvement of about 2000 steps and 500 steps comparison with WMMA's amd DPSO-WMMA's, respectively. The mean square error(MSE) of DPSO-WWMMA has a drop of about 2dB comparison with WMMA's and DPSO-WMMA's. The output constellations of the DPSO-WWMMA is clearer and more compact than the WMMA's and DPSO-WWMMA's. Accordingly, it has the fastest convergence speed, the clearest output constellations, and the smallest MSE for the QAM signals.



In the experiment the underwater acoustic least phase channel $C = [0.9656 - 0.0956 \ 0.0578 \ 0.2368]$ [16],the transmitted signals were 128QAM, the length of the equalizer was 16, the SNR was 30dB. DB2 orthogonal wavelet was used to decompose the input signal and the level was 3. The initial value of the power was 10, forgetting factor $\beta = 0.99$, MSE(1)=2 .The step-size $\mu_{\text{WMMA}} = 5 \times 10^{-7}$, $\mu_{\text{DPSO-WMMA}} = 2 \times 10^{-7}$, and $\mu_{\text{DPSO-WWMMA}} = 3 \times 10^{-6}$. The 20 times Monte-Carlo simulation results were shown in Fig.3.







(b) Outputs of WMMA



(c) Outputs of DPSO-WMMA



(d) Outputs of DPSO-WWMMA

Figure.3 Simulation results for channel

From the Fig.3, we can know that the convergent speed of the DPSO-WWMMA and DPSO-WMMA have an improvement of about 4000 steps comparison with the WMMA's. The mean square error(MSE) of the DPSO-WWMMA is about -8dB ,the DPSO-WMMA is -6dB and the WMMA is -4dB .The output constellations of the DPSO-WWMMA is clearer and more compact than the WMMA's and DPSO-WMMA's. Accordingly, the DPSO-WWMMA has the fastest convergence speed, the clearest output constellations, and the smallest MSE for the QAM signals.

V. CONCLUSIONS

An orthogonal wavelet dynamic weighted multimodulus blind equalization algorithm based on QAM signals is proposed based on combining dynamic particle swarm optimization global optimization algorithm with wavelet blind equalization algorithm. This proposed algorithm can avoid falling into local convergence and strengthen the equalization performance in a dynamic environment. Simulation results of underwater acoustic channel show that the performance of the proposed algorithm is excellent in reducing MSE and improving convergence speed for QAM signals.

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REFERENCE

- Q.-H. Zhao, J.-S. Zhang, "Adaptive nonlinear channel equalization based on combination neural network for chaos-based communication systems," *Acta Physical Sinica*, vol.7, pp.3996-4006, April 2008.
- [2] A. Özen, I. Kaya, B. Soysal, "Variable step-size constant modulus algorithm employing fuzzy logic controller," *Wireless Personal Communications*, vol.2, pp.237–250, May 2009.
- [3] J.-T. Yuan, T.-C. Lin, "Equalization and carrier phase recovery of CMA and MMA in blind adaptive receivers," *IEEE Trans. Signal Process*, vol.6, pp 3206-3217, June 2010.
- [4] X. Yan, Q. Wang G. Li, et al., "Adaptive blind equalization algorithm with multi-module for high-order QAM realtime multi-domain measurement," *Journal of Electronic Measurement and Instrument*,vol.25,pp.22-28 April 2009.
- [5] D.Wu, L.-D. Ge, B. Wang, et al., "Hybrid blind equalization algorithm for high-order QAM signals," *Journal of Information Engineering University*,vol.11,pp .45-48,May 2010.
- [6] X. -D. Xu, X.-C. Dai, et al., "Weighted multi- modulus blind equalization algorithm for high-order QAM signals," *Journal of Electronics & Information Technology*, vol.6,pp.1352 - 1355,March 2007.
- [7] B. Wang, L.-D. Ge, Y.-J. Huo, "Multi-modulus based hybrid blind equalization algorithm for high-order QAM signals," *Journal of Date Acquisition & Processing*, vol.1,pp.8-14,April 2011.
- [8] Y. Chao, Y.-C. Guo, J. Zhu, "Super-exponential iterative blind equalization algorithm based on orthogonal wavelet packet transform," *ICSP2008 Proceedings. Beijing*, pp.1830–1833, March 2008.
- [9] Y.-C. Guo, Z.-X. Liu, "Blind equalization algorithms based on balance orthogonal multi wavelet transform," *Acta Armamentarii*, vol. 3, pp.279-285, July 2010.
- [10] Q.-Y. Tan, Y.-I. Song, "A missile- borne SAR autofocus method based on quantum particle swarm optimization Algorithm," Acta Armamentarii, vol.7,pp. 838- 846,June 2011.
- [11] Y.-L. Wu, H.-B. Li, Y. -P. Zhao, "A novel constellation design for 2²ⁿ⁺¹ QAM," Journal of Electronics & Information Technology, vol.6, pp.1510-1514, 2010.
- [12] W. -G. Zhao, "BP Neural Network based on PSO Algorithm for Temperature Characteristics of Gas Nanosensor," *Journal of Computers*, vol.7,pp.2318-2323, 2012.
- [13] Yudong Zhang, Shuihua Wang, Lenan Wu, Yuankai Huo "Multi-channel Diffusion Tensor Image Registration via Adaptive Chaotic PSO," *Journal of Computers*, vol.6, pp.825-829, 2012.
- [14] Seyyed Ali Hashemi, Behrouz Nowrouzian, "A Novel Discrete Particle Swarm Optimization for FRM FIR Digital Filters," *Journal of Computers*, vol.7, pp.1289-1296, 2012.
- [15] Y.-B. Zhang, J.-W. Zhao, Y.-C. Guo, et al., "A constant modulus algorithm for blind equalization in α -stable noise," *Applied Acoustics*, vol.7,pp.653-660, June 2010.
- [16] Y.-C. Guo, X.-Q. Zhao, Z.-X. Liu, et al., "A modified T/2 fractionally spaced coordinate transformation blind equalization algorithm," *International Journal Communications, Network and System Sciences*, vol.2,pp. 183-189, May 2010.



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