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Instantaneous Gradient based Dual Mode Wavelet Neural Network Blind Equalization for Underwater Acoustic Channel

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Abstract: To further improve the performance of wavelet neural network blind equalization based on constant modulus algorithm (CMA) cost function, an instantaneous gradient based dual mode between modified constant modulus algorithm (MCMA) and decision directed (DD) algorithm was proposed. The wavelet neural network weights change quantity of the adjacent iterative process is defined as instantaneous gradient. After the network attains convergence, the weights of wavelet neural network achieve a stable energy state and the instantaneous gradient would be zero. Therefore dual mode algorithm can be realized by criterion which set according to the instantaneous gradient. Computer simulation results show that the dual mode wavelet neural network blind equalization algorithm proposed in this paper improves the convergence rate and convergence precision effectively, and it has good tracking ability for underwater acoustic channel.

Keywords: blind equalization, wavelet neural network, underwater acoustic channel, CMA

1 Introduction

In underwater acoustic communication systems, acoustic wave propagates by underwater acoustic channel would bear energy attenuation, Doppler frequency shift, multipath transmission and noise interference, which results in inter-symbol interference (*ISI*) at the receiver that seriously affects the quality of communication [1]. Single carrier time domain equalization technique is one of the key technologies to remove the *ISI* to improve the quality of underwater acoustic communication [2]. The traditional adaptive equalization technique needs sending periodical training sequence that both known for transmitter and receiver, which would waste the limited underwater acoustic channel bandwidth [3], furthermore, under the condition of non-cooperative communication in the military field such as underwater target detection or information interception, there is no training sequence can be used which leads traditional adaptive equalizer to failure. Compared with traditional adaptive equalization technology, blind equalization can realize the communication channel compensation and tracking without any training sequence [4]. As a result, blind equalization can save the bandwidth and avoid equalizer unlocking, and even in the non-cooperative communication conditions it can still ensure equalization effectiveness [5].

Underwater acoustic channel usually has nonlinear characteristic, so neural network blind equalization which is one of the most representative nonlinear algorithm often be used [6]. Wavelet neural network (WNN) takes advantages of neural network and wavelet transform to obtain good performance of blind equalization [7]. However, WNN blind equalization uses CMA cost function still has many deficiencies, such as low convergence rate, big steady residual error and easy to fall into the local minimum value. In order to further improve the performance of WNN blind equalization, some improved algorithms were put forward in succession in recent years, for example, evolutionary algorithm is combined with the application of it for blind equalization, including genetic algorithm (GA), particle swarm optimization (PSO) algorithm and differential evolution (DE) algorithm [8], and so on. WNN blind equalization

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uses evolutionary algorithm to improve the performance at cost of huge computational complexity, which results in practical engineering is difficult to achieve. There are some other improved WNN blind equalization algorithms that use gradient optimization algorithm, such as conjugate gradient algorithm, quasi Newton algorithm and least squares algorithm, and so on. These kind algorithms not only increase the computational complexity, but also require very strict constraints, which leads the algorithm application to become difficult.

Compared with CMA, DD algorithm has faster convergence rate and better convergence precision, meanwhile, the cost function of DD algorithm is convex, which means that DD cost function has only a minimum point, if the algorithm converges to the extreme point is equal to the global convergence. So dual mode blind equalization algorithm combined with CMA and DD algorithm can effectively improve the performance without computational complexity increasing [9]. But if the eye diagram of the received signal is not opened, DD algorithm often divergence or convergence error, therefore, the basic idea of dual mode blind equalization algorithm is that use CMA algorithm to open the eye diagram of the received signals, and then the algorithm switches to the DD algorithm to update the equalizer coefficients. To implement dual mode blind equalization, a reasonable threshold can be set allows the algorithms timely switching. According to the threshold setting difference, different dual mode blind equalization algorithms can be obtained. Because the CMA is less sensitive to the phase information, dual mode blind equalization algorithm would occur error when the algorithm switches to DD algorithm for the phase drift of the received signal, to account for this problem, dual mode blind equalization with MCMA [10] and DD algorithm was proposed in this work. We use the instantaneous gradient change rate to set threshold, and a new dual mode WNN blind equalization algorithm was obtained. at last by using computer simulations under the condition of underwater acoustic channel proved the validity of the algorithm compared with decision circle based dual mode algorithm [11] and sign error based dual mode algorithm [12].

2 Wavelet neural network blind equalization

The principle of WNN blind equalization can be shown as Fig.1 [13]. In Fig.1, $x(n)$ is the input sequence of unknown channel and $h(n)$ is the channel impulse response sequence. The Gauss white noise $n(n)$ adds to the output sequence of the channel and $y(n)$ is obtained. The output sequence of WNN equalizer $\tilde{x}(n)$ can be decided by decoded function $G(.)$ to obtain the recovery sequence $\hat{x}(n)$. Signal transmits by the channel can be written as follows [14]

$$s(n) = x(n) * h(n), \tag{1}$$

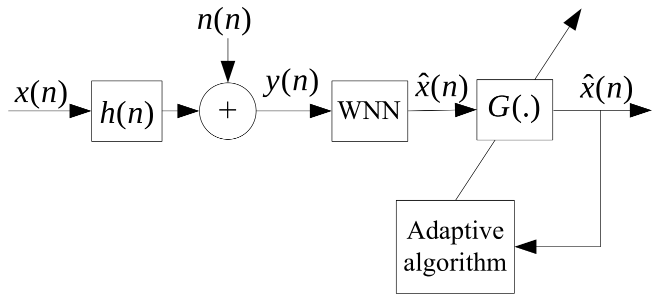

Fig. 1: Block diagram of neural network blind equalization

$$y(n) = s(n) + n(n), \tag{2}$$

If we take $w(n)$ as the equivalent convolution weight coefficients of WNN filter, the output signal can be written as follow

$$\tilde{x}(n) = w(n) * y(n), \tag{3}$$

The purpose of blind equalization is to recover the sending sequence $x(n)$ without the priori information of the sending signal $x(n)$ and the communication channel $h(n)$, and $\tilde{x}(n)$ can be obtained directly by the observed sequence $y(n)$. After equalization, $\tilde{x}(n)$ can be written as follow

$$\tilde{x}(n) = x(n-D) * e^{j\phi}, \tag{4}$$

where D is a constant delay and ϕ is a constant phase shift. The sending sequence recovery quality is not affected by D and the phase shift ϕ can be get rid of by decision set. Combining (1) and (3) and ignoring convolution noise, $\tilde{x}(n)$ can be given as follow

$$\tilde{x}(n) = h(n) * w(n) * x(n), \tag{5}$$

It can be seen that the condition of availability of (4) is that associate impulse response of channel and equalizer must satisfy (6) [15]

$$h(n) * w(n) = [0, \ldots, 0, e^{j\phi}, 0, \ldots, 0], \tag{6}$$

The realization of WNN blind equalization needs to establish network learning cost function by using the received signal, and the weight coefficients are updated by special algorithm which can make the cost function achieve minimum, that is, associate impulse response of equivalent convolution weight and channel satisfies (6). WNN blind equalization takes the cost function of CMA algorithm as the learning cost function to update the parameters of the neural network, while the cost function of CMA just make use of signal high-order statistical property indirectly. Blind equalization by wavelet neural network has slow convergence rate because of adopting error back propagation (BP) algorithms [16], and it is easy to fall into locally minimum point due to non-convexity of the cost function.

WNN blind equalization with three layer is shown in Fig.2, Set the hidden layer input of WNN is $u_j(n)$ and the

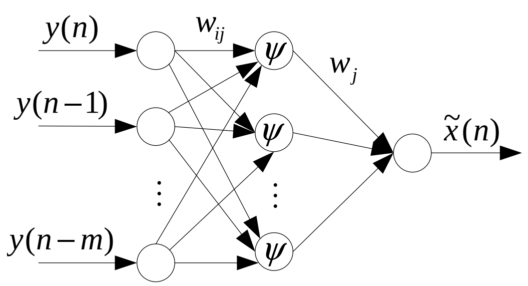

Fig. 2: Tri-level WNN blind equalization

output is $I_j(n)$, the output layer's input is $v(n)$ and the output is $\tilde{x}(n)$, the WNN's state equation can be gotten according to network transmission formula that can be given by

$$u_j(n) = \sum_{i=1}^{m} w_{ij}(n) y(n-i), \tag{7}$$

$$I_j(n) = \psi_{a,b}[u_j(n)], \tag{8}$$

$$v(n) = \sum_{i=1}^{k} w_j(n) I_j(n), \tag{9}$$

$$\tilde{x}(n) = f[v(n)], \tag{10}$$

where $f(.)$ is the transfer function between the input signal and the output signal of the output layer, and $\psi_{a,b}(.)$ is the wavelet transform that act as the input signal of the hidden layer. The transfer function $f(.)$ in this paper is given by

$$f(x) = x + \alpha \sin(\pi x), \tag{11}$$

The derivative function of the transfer function is given by

$$f'(x) = 1 + \alpha\pi\cos(\pi x), \tag{12}$$

The property of the input and the output of the transfer function and its derivative function can be shown as Fig.3 and Fig.4. According to the property of input and output of the transfer function and the derivative function can be seen that the transfer function has a smooth, gradual and monotonic features, which is beneficial to distinguish the input sequence. The parameter $\alpha = 0$ determines the nonlinear characterize of the output of the network, if $\alpha = 0$, the output of network is linear characteristics, and the nonlinear approximation ability of the network is stronger as α becomes larger. However, if α is too larger, the algorithm will be unstable for blind equalization, that

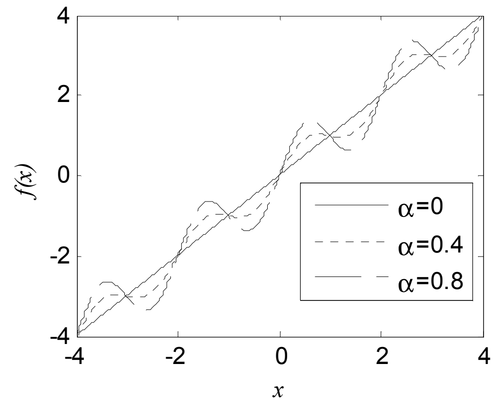

Fig. 3: I/O property of transfer function

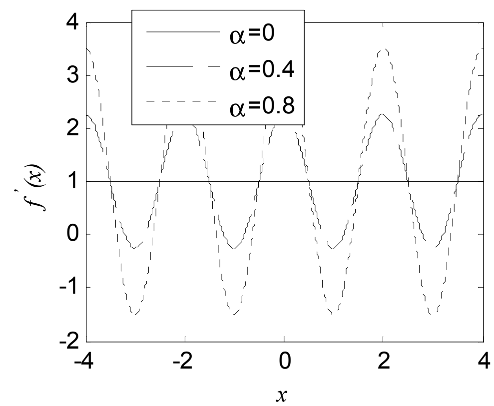

Fig. 4: I/O property of transfer function

is the network output is very sensitive to the nonlinear characteristics. Therefore, in practical applications, it usually selects $\alpha \in (0,1)$.

Combined with CMA blind equalization we can set the cost function of blind equalization by WNN as follow [17]

$$J_D(n) = \frac{1}{2}[|\tilde{x}(n)|^2 - R_{CM}]^2, \tag{13}$$

$$R_{CM} = \frac{E(|\tilde{x}(n)|^4)}{E(|\tilde{x}(n)|^2)}, \tag{14}$$

The network parameters are usually initialized randomly for the gradient descent algorithm to train WNN. Compared with traditional feedforward neural network, the scale factor a_j and the shift factor b_j must be taken into account in the WNN. According to the gradient descent algorithm [18]

$$\mathbf{W}(n+1) = \mathbf{W}(n) - \mu\frac{\partial J_D(n)}{\partial \mathbf{W}(n)}, \tag{15}$$

where μ is the study step.

$$\frac{\partial J_D(n)}{\partial w(n)} = 2[|\tilde{x}(n)|^2 - R_{CM}]\tilde{x}(n)\frac{\partial|\tilde{x}(n)|}{\partial w(n)}, \tag{16}$$

For the output layer

$$\frac{\partial|\tilde{x}(n)|}{\partial w_j(n)} = f'(v(n))I_j(n), \tag{17}$$

$$w_j(n+1) = w_j(n) + \mu K(n)I_j(n), \tag{18}$$

$$K(n) = -2[|\tilde{x}(n)|^2 - R_{CM}]|\tilde{x}(n)|f'(v(n)), \tag{19}$$

For the hidden layer

$$\frac{\partial|\tilde{x}(n)|}{\partial w_{ij}(n)} = f'(v(n))\frac{\partial v(n)}{\partial w_{ij}(n)}, \tag{20}$$

$$\frac{\partial v(n)}{\partial w_{ij}(n)} = w_j(n)\psi'_{a,b}(u_j(n))y_i(n-i), \tag{21}$$

From (20) and (21) we can get

$$\frac{\partial|\tilde{x}(n)|}{\partial w_{ij}(n)} = f'(v(n))\psi'_{a,b}(u_j(n))w_j(n)y_i(n-i), \tag{22}$$

In this paper we take the Morlet wavelet as the wavelet mother function for WNN blind equalizer [20]

$$\psi(x) = xe^{-\frac{1}{2}x^2}, \tag{23}$$

From (23) we can obtain wavelet function as follow

$$\psi_{a,b}(x) = |a|^{\frac{1}{2}}\psi(\frac{x-b}{a}) = |a|^{\frac{1}{2}}\frac{x-b}{a}e^{-\frac{(x-b)^2}{2a^2}}, \tag{24}$$

$$\psi'_{a,b}(x) = |a|^{\frac{1}{2}}\frac{1}{a}e^{-\frac{(x-b)^2}{2a^2}} - |a|^{\frac{1}{2}}\frac{1}{a}(\frac{x-b}{a})^2e^{-\frac{(x-b)^2}{2a^2}}, \tag{25}$$

From (15),(22) and (25) we can obtain the update method of $w_{ij}(n)$ as follow

$$w_{ij}(n+1) = w_{ij}(n) + \mu K_j(n)y(n-i), \tag{26}$$

$$K_j(n+1) = \psi'_{a,b}(u_j(n))w_j(n)K(n), \tag{27}$$

The scale factor a_j and the shift factor b_j can also be updated according to the gradient descent algorithm

$$a(n+1) = a(n) - \frac{\partial J_D(n)}{\partial a(n)}, \tag{28}$$

$$\frac{\partial J_D(n)}{\partial a(n)} = 2[|\tilde{x}(n)|^2 - R_{CM}]|\tilde{x}(n)|\frac{\partial|\tilde{x}(n)|}{\partial a(n)}, \tag{29}$$

$$\frac{\partial|\tilde{x}(n)|}{\partial a(n)} = f'(v(n))\frac{\partial\psi'_{a,b}(u_j(n))}{\partial a(n)}w_j(n), \tag{30}$$

In the similar way we can get the update method of the shift factor b_j.

3 Dual mode wavelet neural network blind equalization

CMA is a special case of Godard algorithm, also it is the most widely used blind equalization algorithm for simple computation and stable performance. But CMA blind equalization convergence rate is slow and has big state steady error after convergence, and it is less sensitive to the phase of the input signal, then a mend CMA (MCMA) was proposed based on CMA. Compared with CMA, MCMA can effectively correct the phase deflection. The cost function of MCMA is given by

$$J_D = \frac{1}{2}[|\tilde{x}_R(n)|^2 - R_R]^2 + \frac{j}{2}[|\tilde{x}_I(n)|^2 - R_I]^2, \tag{31}$$

where $\tilde{x}_R(n)$ and $\tilde{x}_I(n)$ denote the real part and the imaginary part of $\tilde{x}(n)$ respectively, and R_R and R_I is defined as follows

$$\begin{aligned} R_R &= \frac{E(|\tilde{x}_R(n)|^4)}{E(|\tilde{x}_R(n)|^2)} \\ R_I &= \frac{E(|\tilde{x}_I(n)|^4)}{E(|\tilde{x}_I(n)|^2)}, \end{aligned} \tag{32}$$

The cost function of DD algorithm is

$$J_{DD} = \frac{1}{2}[\tilde{x}(n) - \hat{x}(n)]^2, \tag{33}$$

In this paper, dual mode blind equalization algorithm is set according to MCMA and DD algorithm. Define the instantaneous gradient change rate as

$$g(n) = \frac{\|w_{ij}(n) - w_{ij}(n-1)\|}{\|w_{ij}(n-1) - w_{ij}(n-2)\|}, \tag{34}$$

In (34), $\|.\|$ can be computed as follow

$$\|X_{ij}(n)\| = \frac{\sum_{i=1}^{m}\sum_{j=1}^{k}|X_{ij}(n)|}{m \times k}, \tag{35}$$

According to the limit theorem and L'Hospital Rule, if the algorithm stability convergence, then $\lim_{n\to\infty} g(n) = 1$. The instantaneous gradient change rate reflects the network steady state, and it can be used as the threshold for dual mode algorithm switching criterion. Dual mode blind equalization neural network algorithm implement can only change $K(n)$ in the iterative formula. According to MCMA.

$$\begin{aligned} K_1(n) = &-2\{|\tilde{x}_R(n) - R_R|\tilde{x}_R(n) \\ &+ j|\tilde{x}_I(n) - R_I|\tilde{x}_I(n)\}f'(v(n)), \end{aligned} \tag{36}$$

And according to DD algorithm

$$K_2(n) = -2\{\tilde{x}(n) - \hat{x}(n)\}f'(v(n)), \tag{37}$$

Hidden layer weights of neural network are updated according to the error back propagation algorithm without modification. Here according to the instantaneous gradient change rate is given the dual mode neural network weights updating formula

$$w_j(n+1) = w_j(n) + \mu K_m(n) I_j(n), \quad (38)$$

In (38), we choose $m = 1$ if $g(n) - 1 > \delta$ or $m = 2$ if $g(n) - 1 \leq \delta$ to implement the dual mode switching.

4 Simulations and discussion

In the simulations, equivalent probability binary sequence is adopted to act as sending signal and QPSK modulation is utilized. Adding noise is band-limited gauss white noise with zero mean. Typical shallow sea and deep sea underwater acoustic channel [20] are used in our simulations, the channel models have verified by the sea experiment. For the shallow sea channel model, the parameters set as follow: carrier frequency is $10kHz$, channel bandwidth is $2kHz$, transmit baud rate is $1000symbol/s$, wind speed is $20kn$, the sender and receiver locate in underwater 10 meters, and the distance is 5000 meters. For the deep sea channel model, the parameters set as follow: the depth of sea is 5000 meters; sound source is located in 1000 meters underwater, receiver is located in the 900 meters underwater, the distance between sound source and receiver is 56 kilometers, carrier frequency is $1kHz$, transmit baud rate is $100symbol/s$, the parameters of eight rays of the channel model can be shown as Tab.1.

Table 1: The parameters of the channel

Ray No	shallow sea channel		deep sea channel	
	t/ms	A	t/ms	A
1	0.000	1.0000	0.0000000	0.4954
2	0.026	-1.0000	0.0265385	-0.1464
3	0.026	-0.3286	0.0319367	0.5079
4	0.100	0.3286	0.0647739	-0.1555
5	0.100	0.3286	0.2056037	0.8399
6	0.240	-0.3286	0.2320864	1.0000
7	0.420	-0.1080	0.2359591	0.6914
8	0.420	0.1080	0.3671784	0.2187

The structure of WNN blind equalizer set to $30 \times 15 \times 1$. The diagonal elements of weights between the input and the hidden layer and the center elements of weights between the hidden and the output layer are initialized to 1, the other weights set to 0. The step size $\mu = 0.0012$. The comparison is in terms of mean square error (MSE) [21] which is defined as follow

$$MSE(n) = \frac{1}{n}\sum_{k=1}^{n} |\tilde{x}(k) - \hat{x}(k)|^2, \quad (39)$$

In order to verify the performance of the dual mode WNN blind equalization (DUAL-IG) proposed in this paper, MCMA, dual mode based decision circle blind equalization (DUAL-DC) and dual mode based sign error blind equalization (DUAL-SE) is done in the simulation for comparison. Fig.5 shows the convergence curve of the four method mentioned above with $SNR = 20.5dB$ for the shallow sea channel and Fig.6 shows the convergence curve of the four method mentioned above with $SNR = 23.2dB$ for the deep sea channel. From Fig.5 and Fig.6 we can see that DUAL-IG has the fastest convergence rate and the lowest MSE in the shallow sea and the deep sea channel. DUAL-IG algorithm proposed in this work convergence rate faster about 1000 iterative times than DUAL-DC in the shallow sea channel and faster about 200 iterative times than DUAL-DC in the deep sea channel. Fig.7 and Fig.8 show the bit error rate (BER) of the four methods in the simulations, which show that DUAL-IG has the lowest BER in the four blind equalization algorithms.

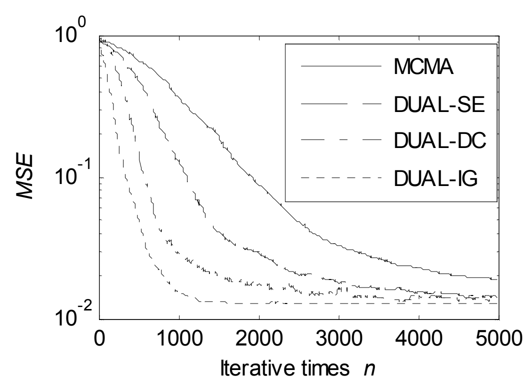

Fig. 5: MSE in shallow sea channel

5 Conclusions

In this study a new dual mode WNN blind equalization algorithm based on the instantaneous gradient change rate was proposed, the theory analysis shows that the instantaneous gradient change rate reflects the stability of the WNN blind equalizer and the threshold can be set according to it. Simulation results prove that the proposed algorithm has good equalization performance and has good tracking ability for underwater acoustic channel, therefore this work has a certain practical value.

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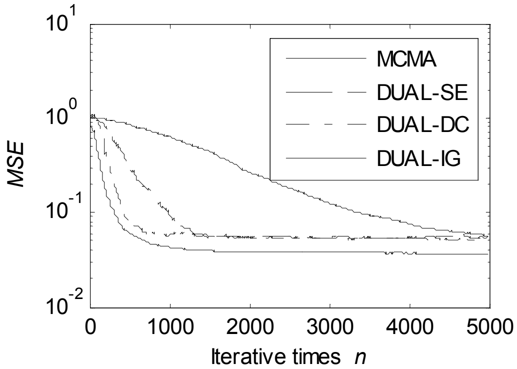

Fig. 6: *MSE* in deep sea channel

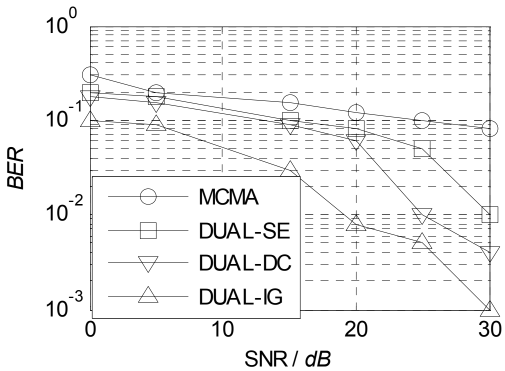

Fig. 7: *BER* in shallow sea channel

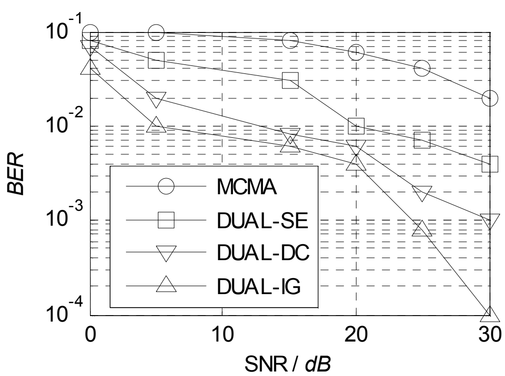

Fig. 8: *BER* in deep sea channel

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