Clonal Selection Algorithm for IIR Equalizer Design

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ABSTRACT

In this paper, the constant modulus (CM) criterion is used to design IIR equalizer. For counterbalancing the interference of the channel, Clonal Selection Algorithm (CSA) is employed to optimize the coefficients of transfer function of the equalizer. CSA, the essence of Immune Algorithm (IA), is effective to solve complexly numerical problems. Besides, we also use the stability triangle method to ensure the system is stable. The simulation results demonstrate the good performance of the equalizer designed by CSA to reconstruct the signal transmitted.

Categories and Subject Descriptors

G.1.6 Optimization

General Terms

Algorithms

Keywords

Clonal selection algorithm, Constant modulus,

IIR equalizer, Stability triangle

1. INTRODUCTION

Equalization is a common strategy to the noxious effects of communication channels on the information transmitted. The central issue of such process is the design of a filter, namely, equalizer, capable of counterbalancing the interference of the medium.

A successful approach to deal with the IIR filter adaptation has been genetic algorithm (GA), which can be interpreted as evolutionary optimization techniques[1]. There is a premature drawback in GA, so researchers try to use another effective algorithm to obtain optimal coefficients. By combining the CM criterion with the IA, the literature introduces a novel framework to obtain the optimal receiver[2, 3].

Inspired by antigen-antibody reaction of the biological immune system, IA attracts a lot of interest in solving complicated problem in many ways, including machine-learning, pattern-recognition tasks and adapted to optimization etc[4]. CSA is the quintessence of IA, and they are very similar to each other. The difference between the two of them is that IA considers the affinity between not only antibody (Ab) and antigen (Ag) but also Ab and Ab. Since CSA executes the mechanisms, selection and hyper-mutation, twice for each generation, it is able to obtain global solution but not local solution[5]. In the other words, the main advantage of using CSA is the fine tuning to obtain optimal solution.

The paper is organized as follows. In section 2, the relation between channel and equalizer is presented in detail. Section 3 introduces the artificial immune system and its essence, clonal selection algorithm and its regulations. And the design approach is presented in section 4. Section 5 discusses the experimental results for examples of IIR filter. Finally, section 6 concludes the paper briefly.

2. CHANNEL AND EQUALIZER

The main duty of communication systems is to assure to provide adequate message interchange, through a certain channel, between a transmitter and a receiver. The distortion takes place in the process of transmitting message, and it usually leads to severe degradation. Consequently we need a device named equalizer filters to recover the desired information from the received signal. Figure 1 depicts the schematic channel and equalizer representation in a communication system, together with their respective input and output signals[2, 3].

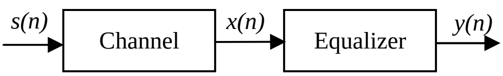

Figure 1. Simplified Model of a Communication System

From Figure 1, it can be inferred that the main goal of the equalizer is to obtain an output signal as similar as possible to the transmitted signal, except for a gain K and a delay d, that is,

$$y(n) = K \cdot s(n-d) \tag{1}$$

which is well-known zero-forcing (ZF) condition.

In most applications the equalizers are implemented using linear filters mainly due to their simplicity. They can be divided into two major c1asses: FIR filters and IIR filters. FIR filters are feedforward structures, and their input-output relation are given by:

$$y(n) = \mathbf{w}^T \cdot \mathbf{x}(n) \tag{2}$$

where **w** is the equalizer coefficient vector of length L and $\mathbf{x}(n) = [x(n)x(n-1)\cdots x(n-L+1)]^T$ is the input vector.

The central task is to obtain the parameters of the chosen equalizer in order to accomplish a condition close to the ZF one. If it is possible to count on a priori knowledge of the channel impulse response, the task becomes purely mathematical.

FIR filters are inherently stable and easily describable in mathematical terms. However, they are limited structures, incapable of perfectly inverting another FIR system. This limitation arises from the “all-zero” character of a FIR transfer function.

Such drawback is the rationale behind the use of IIR equalizers. These are recurrent linear filters characterized by the following input-output relation:

$$y(n) = \mathbf{w}^T \mathbf{x}(n) - \mathbf{b}^T y(n-1) \tag{3}$$

where **b** is the feedback parameter vector, $y(n-1) = [y(n-1)y(n-2)\cdots y(n-M+1)]^T$ is the feedback input vector, and M is the feedback order. The presence of a feedback term enhances the capability of a linear filter, allowing the controlled placement of poles as well.

When information about the transmitted signal is, at least for some time, at hand, it is possible to make use of the Wiener criterion, based on the following mean square error (MSE) cost function:

$$J_W = E\{[s(n-d) - y(n)]^2\} \tag{4}$$

where *d* is the previously defined equalization delay. Given a certain delay *d*, *Jw* has a single minimum, called the Wiener solution. As a rule, each Wiener solution possesses a distinct MSE. This accounts for an important assertion: if the equalization delay is supposed to be a variable, then *Jw* has several minima (multiple local optima). Among these many optima, there is, usually, a single optimal Wiener solution, associated with an optimal delay.

As can be deduced from the comparison between Eq(1) and Eq(4), the Wiener criterion is strongly related to the ZF condition. Hence, the determination of the optimal Wiener solution is very important and has a great practical appeal. However, there are two main difficulties: the use of samples of the transmitted signal and the choice of *d*.

The drawback associated with the dependence on a “pilot signal” was the main motivation behind the proposal of blind techniques, that is, criteria which do not make use of samples of $s(n)$. Among these, the CM criterion has received special attention. Its cost function is given as follows:

$$J_{CM} = E\{[R_2 - |y(n)|^2]^2\} \qquad (5)$$

where

$$R_2 = \frac{E[|s(n)|^4]}{E[|s(n)|^2]} \qquad (6)$$

The cost function presented in (5) has multiple minima, except in some trivial cases. Recent studies [6, 7] have pointed in the direction of an intimate relationship between these minima and some Wiener solutions (the best ones). In other words, these works indicate that a linear feed-forward structure, the multiple minima of the function (5) are close to the best of Weiner solutions. We will assume that the same holds for a linear structure, based on the conjecture that linearity is the link between CM recovery and Wiener equalization. This is the core of the CM part of the framework proposed here.

3. CLONAL SELECTION ALGORITHM

An artificial immune system (AIS) which is based upon models of the natural immune system. This natural system is an example of an evolutionary learning mechanism which possesses a content addressable memory and the ability to desert little-used information. IA[8], modeled mathematically the immune diversity, network theory and clonal selection as a multi-modal function optimization problem. The guide of diversity and multiple solution vectors instituted were kept as memory of the system. The role of the biological immune system is to provide the organisms with an effective mechanism against pathogenic infections [9]. There are two defensive lines in the biological immune system, one is the innate immune system, and the other is the adaptive immune system. The principal theory of the adaptive immune response is the clonal selection theory. From the perspective of the Darwin’s evolution theory, the clonal selection can be explained as a microevolution in the immune system.

The clonal selection algorithm has two main computational mechanisms, which are selection and mutation. Proposed by Leandro N. de Castro and Fernando J[3, 5]. Von Zuben firstly, the two mechanisms in CSA are completed by taking into account the immune properties. In other words, proliferation and mutation rate are proportional to the affinity.

(5)

(6)

Just like the relation between the key and lock, antibody and antigen must suit with each other, then the response will work.

The individual steps of CSA are described as follows, and the figure 2 shows the flow chart:

1) Initial condition: create the first iteration antibodies (Abs) randomly.

2) Calculating the fitness (f) that represents the affinity between the antigen (Ag) and Abs.

3) To select part of Abs with higher fitness to reproduce (clone) and mutate.

4) Calculating fitness (f*) of the new group of Abs after mutating.

5) Selecting numbers of new Abs (Abs*) with higher fitness (f*) again, and storing them that are better solutions in each iteration in memory cells.

6) Reproduction of Abs, which are composed of Abm (Abs* in memory cells) and some new random Abs (Abd) that substitute for old Abs (Abr) suppressed previously.

7) Repeat steps 2nd to 6th until complete the iterations set before.

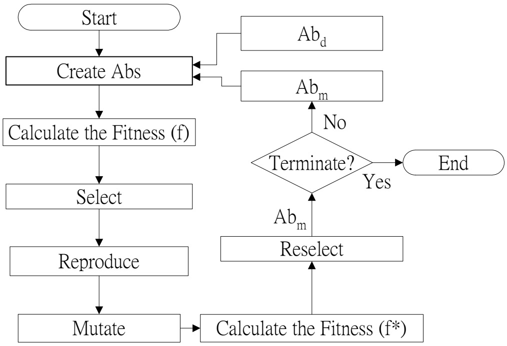

Figure 2 The flow chart of CSA

4. DESIGN APPROACH

The CM criterion is broadly studied blind equalization technique[6, 10, 11]. The last twenty years have seen the proposal of many relevant works scrutinizing the basis of the CM criterion and its relation to other criteria[3]. These works pointed out two aspects that deserve to be highlighted [6, 7]:

(1) The CM cost function is multimodal.

(2) There is an intimate relationship between CM minima.

Combined with the CM criterion, a very robust blind adaptive framework, the CSA will be proposed in this paper to perform optimal blind IIR equalization. Consider a third order typical pulse transfer function, and we can simplify the third order transfer function by first and second order form:

$$H(z) = K\frac{b_0 + b_1 z^{-1} + b_2 z^{-2} + b_3 z^{-3}}{a_0 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3}}$$

$$= K\frac{(p_0 + p_1 z^{-1})(1 + p_2 z^{-1} + p_3 z^{-2})}{(1 + q_1 z^{-1})(1 + q_2 z^{-1} + q_3 z^{-2})} \quad (7)$$

where K is a gain, and ai, bi, pi, qi for i= 1, 2, 3 are the coefficients.

The coefficients of the formulation can be represented the element of the single antibody.

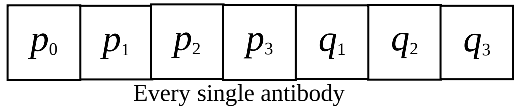

Figure 3 Antibody with coefficients

In theory, such a antibody formulation may proceed to the paratope operation, and each newly generated antibody can be considered as a potential solution to *H(z)*. Nevertheless, the numerical values of paratopes may destabilize the filter if their values are not restricted. Since the filter is formed by a combination of first and second order models, the coefficients of the model can be within a stable region of a unit circle in the *z* plane. Hence, the coefficient of the first order model is simply limited to (-1, 1), whereas the second order model needs a specific subroutine to realize such a confinement. In this case, the coefficients of the denominator ($1 + q_2 z^{-1} + q_3 z^{-2}$) must lie within the stability triangle [10, 11]. In the stability triangle, the parameter of q_3 can be initially set to its possible range, (-1, 1), and q_2 is then assigned as a randomly generated number within the range (-1- q_3, 1+ q_3), so that stability is ensured. In the same way, we can simplify the high order polynomial form in the denominator by first and second order form, and so forth. So the stability of the high order system can be maintained[12, 13].

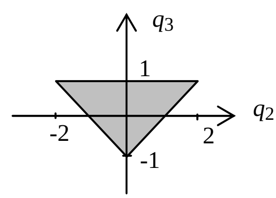

Figure 4 Stability triangle

The fitness function, J_{FIT}, is given by the following mapping:

$$J_{FIT} = \frac{1}{1 + J_{CM}} \quad (8)$$

The basic idea behind this conversion is to transform minima into maxima. We used the CSA, as discussed in previous section, to obtain the CM global minimum for the transmitting channels. The fitness proportional mutation is performed according to the following expression[2]:

$$c' = c + \frac{1}{\beta}\exp(-f^*)\cdot N(0,1) \qquad (9)$$

where c' is a mutated antibody c, $N(0,1)$ is a Gaussian random variable of zero mean and standard deviation $\sigma = 1$, β is a parameter that controls the decay of the inverse exponential function, and *f** is the fitness of an individual normalized in the domain range. So the equation (9) is based upon a Gaussian mutation that accounts for a fitness proportional mutation.

5. SIMULATION RESULTS AND DISCUSSIONS

In the simulation, we consider that the samples of the transmitted signal assume the values between positive one and negative one. The parameters in CSA are set as follows: size of population S=20, total generations G=1000, memory cells M=6, and the reproduction index N=6.

In the experiment, $H_C(z)$ is the transfer function of the chosen channel. After executing CSA, the second, third and forth order transfer function of IIR equalizer are show as Table 1. Besides, we also try to add the AWGN noise to test the performance of the IIR equalizer design with CSA. The model of communication system shows as Figure 5. The learning curve of CSA for optimizing the numerical parameters of second, third and forth order IIR equalizers are shown as Figure 6, 7, 8. The poles of the IIR equalizers are within the unit circle, so the systems we design are stable. The channel and equalizer frequency response are shown as Figure 9, and the frequency response via channel and three different order equalizers are illustrated in Figure 10.

$$H_C(z) = \frac{1 + 0.6z^{-1} + 0.18z^{-2} + 0.504z^{-3} + 0.1856z^{-4}}{1 - 0.6z^{-1} + 0.25z^{-2}}$$

We define the SNR as follows:

$$SNR = -10\log E[n^2(k)] \qquad (10)$$

where *n(k)* is AWGN noise. The relation curve between the BER and SNR of the system with equalizer and without equalizer are illustrated in Figure 11.

6. CONCLUSION

In this paper, a method combined by the constant modulus criterion, clonal selection algorithm and stability triangle method is presented to design the IIR equalizer. We can easily obtain the optimal coefficients of transfer function of the equalizer by CSA, and the stability triangle method limits the range of coefficient values to ensure the system designed by our method is stable. The learning cure demonstrates our method is efficient and reliable. Although the equalizer is able to ensure AWGN noise additively in transmission process, its performance is not good enough, and that is also our next step to improve the efficacy of the system in the further work.

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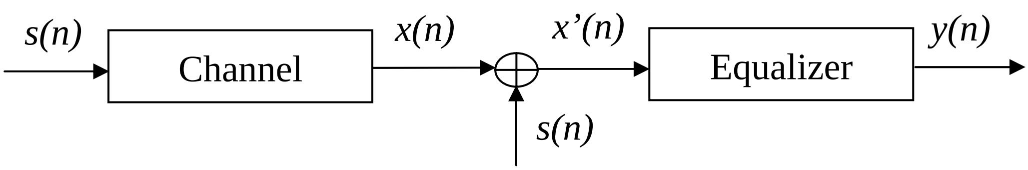

Figure 5. Simplified Model of a Communication System with AWGN noise

Table 1. Results of experiment

Order	Transfer function	Zeros	Poles
Second	$H_{E2}(z)=\dfrac{0.9326-0.3873z^{-1}-0.1661z^{-2}}{1+0.795z^{-1}-0.043z^{-2}}$	*0.6780*	*-0.8458*
		-0.2627	*0.0508*
Third	$H_{E3}(z)=\dfrac{-0.9956+0.9834z^{-1}-0.6535z^{-2}+0.1856z^{-3}}{1+0.2097z^{-1}+0.131z^{-2}+0.5453z^{-3}}$	*0.2690+j0.5849*	*-0.8349*
		0.2690-j0.5849	*0.3126+j0.7452*
		0.4498	*0.3126-j0.7452*
Forth	$H_{E4}(z)=\dfrac{0.9999-0.962z^{-1}+0.6097z^{-2}-0.2572z^{-3}+0.0781z^{-4}}{1+0.237z^{-1}+0.1043z^{-2}+0.4394z^{-3}-0.0237z^{-4}}$	*0.0277+j0.5147*	*-0.8147*
		0.0277-j0.5147	*0.2623+j0.6916*
		0.4533+j0.2971	*0.2623-j0.6916*
		0.4533-j0.2971	*0.0531*

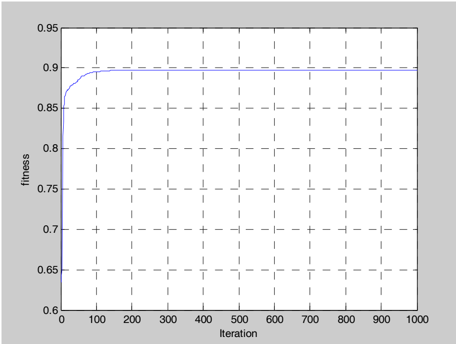

Figure 6. Learning curve, the relation between fitness and iteration of the second order equalizer

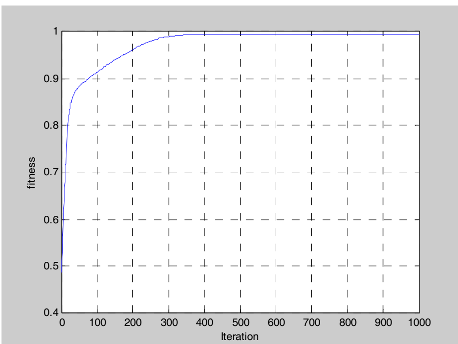

Figure 7. Learning curve, the relation between fitness and iteration of the third order equalizer

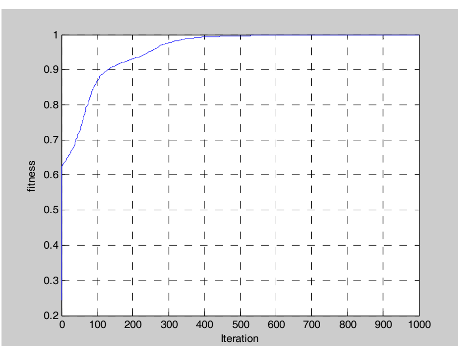

Figure 8. Learning curve, the relation between fitness and iteration of the forth order equalizer

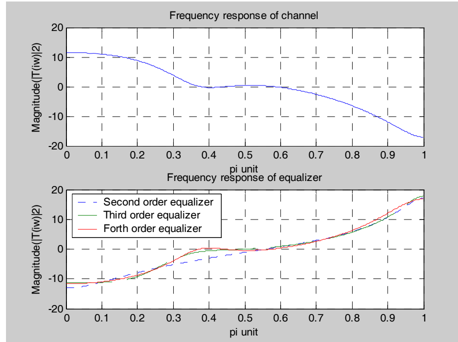

Figure 9. Frequency response of the channel and equalizers

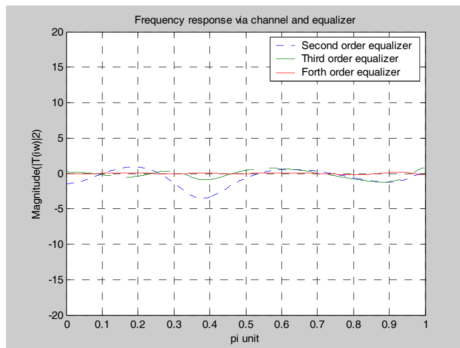

Figure 10. Frequency response via channel and three equalizers

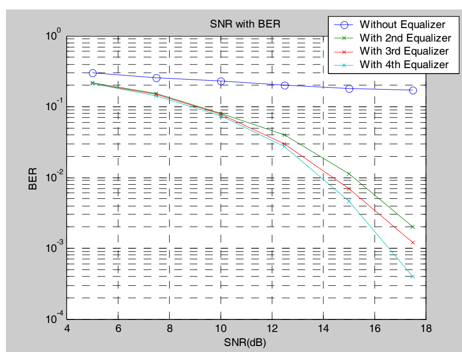

Figure 11. Relation between SNR and BER