Editors:

Fun Shao, Wise Shu & Tracy Tian

ELECTRIC, ELECTRONIC AND CONTROL ENGINEERING

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Electric, Electronic and Control Engineering

Editors

Fun Shao

Digital Library Department, Library of Huazhong University of Science and Technology, China

Wise Shu

Art College, Hubei Open University, China

Tracy Tian

Bos'n Academic Service Centre, China

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Preface

Electric, Electronic and Control Engineering contains the contributions present at the 2015 International Conference on Electric, Electronic and Control Engineering (ICEECE 2015, Phuket Island, Thailand, 5–6 March 2015). The book is divided into four main topics:

- Electric and Electronic Engineering
- Mechanic and Control Engineering
- Information and Communication Technology
- Environmental and Industrial Technology

Considerable attention is also paid to education science, chemical engineering, hydraulic engineering and civil engineering, etc. The book will be useful and invaluable to professionals and academics in electric & electronic, mechanic & control engineering and information & Communication and environmental & industrial technology.

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Adaptive algorithm of parallel genetic optimization based on orthogonal wavelet of space diversity

Xiaogen Pei
Communication Command Department of the Armored Force Institute, Bengbu, China
School of Information Science and Engineering, Shandong University, Jinan, China

Shaohua Zheng
Communication Command Department of the Armored Force Institute, Bengbu, China

ABSTRACT: Diversity technology can effectively resist channel multipath fading, and balanced technology can effectively inhibit the inter-symbol interference, so the diversity technology and balanced technology combined can effectively improve the quality of communication. Simultaneously, this paper uses parallel genetic algorithm to optimize the space diversity orthogonal wavelet adaptive algorithm, taking the space points on each branch equalizer weight vector as the son species of parallel genetic algorithms for selection, crossover, and mutation; between each species to each other and regularly send the best individual fitness; eliminate the worst individual fitness; and take diversity branch output signal and input orthogonal wavelet adaptive device combined. The computer simulation results show that the fast algorithm convergence speed and small steady-state errors can achieve the global optimal solution.

KEYWORDS: Parallel genetic algorithm; Space diversity; Wavelet transform; Adaptive.

1 INTRODUCTION

In a communication system, the channel's multipath fading and the transmission time delay phenomenon seriously affect the reliability of digital communication between transmitter and receiver. An effective method that is used for eliminating the channel fading is adopting diversity technology, which includes frequency diversity, time diversity, and space diversity, compared with the spatial diversity, frequency diversity, and time diversity that will take up too much bandwidth. And the adaptive technology is one of the most effective ways to overcome the inter-symbol interference, so the combination of space diversity and adaptive technique can effectively overcome channel fading and inter-symbol interference, thus improving the performance of the communication system [1]. Through orthogonal wavelet transform, orthogonal wavelet adaptive algorithm can reduce the correlation between signal and noise, thus accelerating the convergence speed [2]. However, the initialization of an adaptive algorithm for weight vector is sensitive, which makes the algorithm easily fall into the local minimum value and even divergence [3].

Genetic Algorithm (GA) provides a generic framework for solving complex system optimization problems, and it does not depend on problems of specific areas; problems of species have a strong robustness. However, the traditional genetic algorithm efficiency is not high and is easy in premature convergence. The parallel genetic algorithm using a traditional genetic algorithm intrinsic parallel mechanism aims at improving the accuracy of the algorithm efficiency and the precision of the solution, avoiding premature convergence, and accelerating convergence speed [4].

On the basis of the earlier analysis, this paper will have reference to the parallel genetic algorithm based on the orthogonal wavelet adaptive algorithm of space diversity; by using the parallel genetic algorithm for the spatial diversity equalizer, the weight vector of each branch is optimized, which is the diversity branch output signal input orthogonal wavelet adaptive device after the merger. The computer simulation shows that the fast algorithm convergence speed and small steady-state errors can get the global optimal solution.

2 NORM OF THE ADAPTIVE ALGORITHM BASED ON ORTHOGONAL WAVELET TRANSFORM

The norm of the adaptive algorithm based on orthogonal wavelet (WTCMA) principle is shown in figure 1.

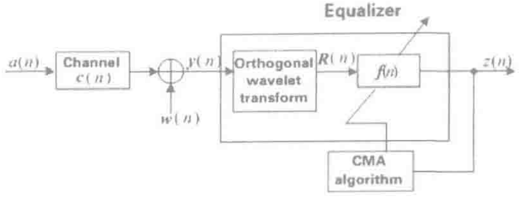

Figure 1. Adaptive algorithm based on orthogonal wavelet transform.

In figure 1, n shows the time sequence, $\boldsymbol{a}(n)$ shows the launch signal, $\boldsymbol{c}(n)$ shows the channel impulse response, $\boldsymbol{w}(n)$ shows the channel output of additive white Gaussian noise, $\boldsymbol{y}(n)$ shows the equalizer input signal, $\boldsymbol{R}(n)$ shows the signal after orthogonal wavelet transform, $\boldsymbol{f}(n)$ shows the equalizer weight vector, and $z(n)$ shows the signal after equilibrium.

The norm of the adaptive algorithm of orthogonal wavelet transform for the cost function is as follows:

$$J(\boldsymbol{f}) = E\{[R_2 - |z(n)|^2]^2\} \tag{1}$$

$$R_2 = \frac{E(|a(n)|^4)}{E(|a(n)|^2)} \tag{2}$$

$$z(n) = \boldsymbol{f}^H(n)\boldsymbol{R}(n) \tag{3}$$

$$\boldsymbol{R}(n) = \boldsymbol{Q}y(n) \tag{4}$$

$$\boldsymbol{f}(n+1) = \boldsymbol{f}(n) + \mu\hat{\boldsymbol{R}}^{-1}(n)\boldsymbol{R}(n)e(n)z^*(n) \tag{5}$$

$$e(n) = z(n)[|z(n)|^2 - R_2] \tag{6}$$

In the formula, $\boldsymbol{Q}$ shows the orthogonal wavelet transform matrix, superscript H shows conjugate transpose, $e(n)$ shows the error function, μ shows the step length, $\hat{\boldsymbol{R}}^{-1}(n) = \mathrm{diag}[\sigma^2_{j,0}(n), \sigma^2_{j,1}(n), \ldots, \sigma^2_{j,k_j}(n), \sigma^2_{J+1,0}(n), \ldots, \sigma^2_{J,k_J}(n)]$, among them $\sigma^2_{j,k_j}(n)$, $\sigma^2_{J+1,k_J}(n)$, respectively, for $r_{j,k}(n)$, $s_{J,k}(n)$ of the average power estimation. By the following recursive formula, we get:

$$\begin{cases} \hat{\sigma}^2_{j,k}(n+1) = \beta\hat{\sigma}^2_{j,k}(n) + (1-\beta)|r_{j,k}(n)|^2 \\ \hat{\sigma}^2_{J+1,k}(n+1) = \beta\hat{\sigma}^2_{J+1,k}(n) + (1-\beta)|s_{J,k}(n)|^2 \end{cases} \tag{7}$$

However, the WTCMA algorithm has easy convergence to the local minimum points, and the performance of channel fading resistance is poor. In order to overcome the WTCMA performance defects, in combination with the parallel genetic algorithm, the space diversity, and orthogonal wavelet adaptive algorithm, the adaptive performance should be improved.

3 BALANCE TECHNOLOGY BASED ON SPACE DIVERSITY

3.1 *Spatial diversity equalizer*

Space diversity also calls the antenna diversity and uses more of the diversity form in the communication, in simple terms, uses multiple receiving antennas to receive signals [5]. Because the decline of each primitive received signal can be regarded as independent of each other, and the fading probability of all channel colleagues is very low, so the space diversity technology is one of the effective ways to eliminate the decline. As a result, the space diversity technology is applied to the adaptive equalizer and can effectively overcome the channel fading and inter-symbol interference. Spatial diversity equalizer (SDE) principle is shown in figure 2.

In figure 2, $\boldsymbol{a}(n)$ is independent with the distribution of the emission signal sequence $\boldsymbol{c}_l(n)$ is the NO. l road channel of impulse response vector:

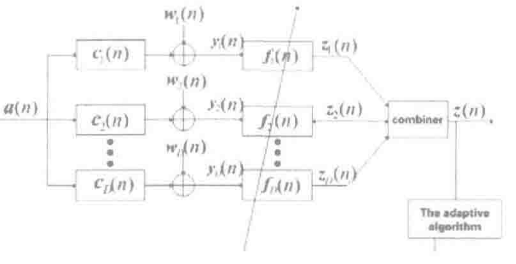

Figure 2. Spatial diversity equalizer structure.

$\boldsymbol{w}_l(n)$ is the NO. l road of Gaussian white noise sequence; $\boldsymbol{y}_l(n)$ shows the NO. l road of input signal vector; $\boldsymbol{f}_l(n)$ is the NO. l road of the equalizer's weight vector; among them, $\boldsymbol{M}_f$ shows the length of the equalizer; $z_l(n)$ is the NO. l road of the output of the equalizer; and among them, $z(n)$ shows the combined output signal.

Figure 2 shows that the adaptive spatial diversity in each branch is made up of sub-channels and the sub-adaptive device. Signals are received through the sub-channel and the sub-equalizer to merge processing; merging processing methods have a choice to merge, with maximal ratio combination and an equal-gain merger. Among them, the equal-gain merger is the most easy to implement, so this article will use an equal-gain merger method.

3.2 *Adaptive algorithm of space diversity based on equal-gain merger*

Two paths of the equal-gain merger of space diversity adaptive device structure are shown in figure 3.

According to the figure, two paths of the equal-gain spatial diversity equalizer contain two prior to filters (each path set a filter) $f_F^{(i)}(n)$ and a rear filter f_B (n). Weight vector of three filters is united by the adaptive algorithm based on decision feedback adjustment, then

$$z(n) = \sum_{i=1}^{2} y^{(i)}(n)[f_F^{(i)}(n)]^T - \hat{a}(n-1) f_B(n) \tag{8}$$

$$f_F^{(1)}(n+1) = f_F^{(1)}(n) - \mu_F z(n)[|z(n)|^2 - R^2]\ [y^{(1)}(n)]^* \tag{9}$$

$$f_F^{(2)}(n+1) = f_F^{(2)}(n) - \mu_F z(n)[|z(n)|^2 - R^2]\ [y^{(2)}(n)]^* \tag{10}$$

$$f_B(n+1) = f_B(n) - \mu_B z(n)[|z(n)|^2 - R^2]\hat{a}^*\ (n-1) \tag{11}$$

Taking the just cited equal-gain merger of space diversity adaptive device apparatus for EG – SDE,

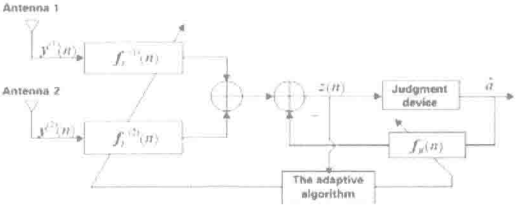

Figure 3. Equal-gain merger of space diversity adaptive device structure.

4 INTRODUCING PARALLEL GENETIC OPTIMIZATION OF SPACE DIVERSITY WAVELET ADAPTIVE ALGORITHM

4.1 *Parallel genetic algorithm*

Parallel Genetic Algorithm (PGA) is a suitable kind for complex constrained optimization problem of global optimization ability. Parallel genetic algorithm mainly has three categories: (1) the master–slave parallel genetic algorithm; (2) coarse-grained degree parallel genetic algorithm; and (3) fine-grained degree parallel genetic algorithm[6]. Among them, the coarse-grained parallel genetic algorithm distributes several sub-populations to their corresponding processor; each processor has not only independent calculation fitness but also independent selection, restructure crossover, and mutation operation, and regularly sends each other the best individual fitness, thus speeding up to meet the requirements of the termination conditions. Currently, it is the most widely used parallel genetic algorithm [7].

Migration is a parallel genetic algorithm introduced into a new operator that points to the course of evolution of neutron population exchange between individual processes; the general migration method sends the best individual in the group to other subgroups. Through migration, it can accelerate better individuals in the group communication, improve convergence rate and precision of the solution[8]. Compared with the single population, only a small number of individual evaluation calculation workload is needed. As a result, even with a single processor, in a serial way (pseudo parallel), a computer could implement the parallel algorithm, thus producing good results [9]. So, the use of a migration operator makes the parallel algorithm more suitable for global optimization with a small amount of calculation.

The most basic migration model is the ring topology model, and individual transfer occurs only in the adjacent sub-population. In the adjacent transfer model, the transfer occurs only in the close neighbor set. The models are shown in figure 4.

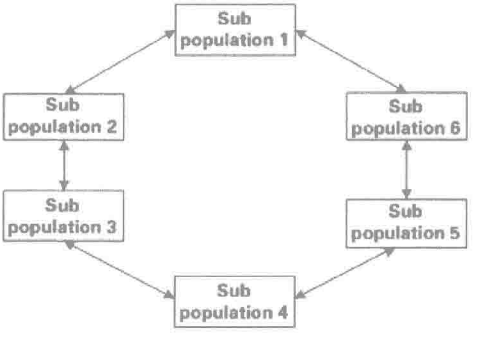

Figure 4. Ring topology model figure.

This article considers the combination of the coarse-grained degree parallel genetic algorithm based on migration of ring topologies, space diversity, and orthogonal wavelet transform and adaptive algorithm; the parallel genetic algorithm has fast convergence speed, global optimal solutions, and orthogonal wavelet transform that reduce the correlation of signal and noise to the space diversity adaptive algorithm. These are optimized by an equal-gain merger, and we get the space diversity orthogonal wavelet adaptive algorithm based on parallel genetic optimization.

4.2 *Space diversity orthogonal wavelet adaptive algorithm based on parallel genetic optimization*

By reference to the parallel genetic algorithm and the orthogonal wavelet transform based on the equal-gain merger of adaptive algorithms, we get the spatial diversity based on parallel genetic optimization; this algorithm has a high convergence rate, precision of solution, and we can get the global optimal solution. Three paths of space diversity orthogonal wavelet adaptive algorithm based on parallel genetic optimization principles are shown in figure 5.

In the figure, n shows the time sequence, $\boldsymbol{a}^{(i)}(n)$ shows the NO. i road launch signal, $\boldsymbol{c}^{(i)}(n)$ shows the NO. i road channel impulse response, $\boldsymbol{w}^{(i)}(n)$ shows the NO. i road channel output end additive Gaussian white noise, $\boldsymbol{f}_F^{(i)}(n)$ shows the NO. i road pre-equalizer weight vector, $\boldsymbol{y}^{(i)}(n)$ shows the NO. i road output signal, $\boldsymbol{y}(n)$ shows the signal after the equal-gain merger, $\boldsymbol{z}(n)$ shows the output signal, $\boldsymbol{f}_B(n)$ shows the orthogonal wavelet adaptive device weight vector, and $\boldsymbol{J}^{(i)}(f_m)$shows the NO. i road parallel genetic algorithm's son population of cost function.

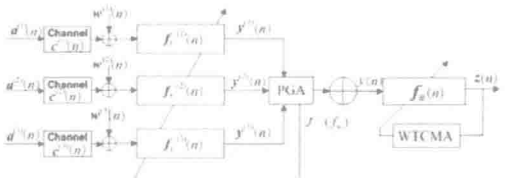

Figure 5. Block diagram of space diversity principle orthogonal wavelet adaptive algorithm based on parallel genetic optimization.

In this algorithm, three forward equalizers are contained (each path set an equalizer), with each branch of the equalizer weight vector as the decision variable of parallel genetic algorithms, the design initial population $Chrom^{(i)}=[\boldsymbol{f}_1,\boldsymbol{f}_2,\cdots,\boldsymbol{f}_M]$, of which M is individual number. In the population of every individual, $\boldsymbol{f}_m(1\le m\le M)$ corresponds to a balancer weight vector. This paper constructs the initial population based on the characteristics of parallel genetic algorithms, namely there are three son populations, with each son population corresponding to a path. Considering the characteristics of the adaptive, the weight vector of each module value will be less than 1, so will the search as the [0, 1].

Assuming the received signal sequence of length for N, using the time average instead of the statistical average, formula (1) often shows that the constant model algorithm of the cost function can be calculated by the following formula:

$$J^{(i)}(f_m)=\frac{\sum_{j=1}^{N}(R-|y_m^{(i)}(j)|^2)^2}{N} \qquad (12)$$

In the formula, m shows the equalizer weight vector of individual serial number, N shows the received signal sequence length for each generation, i shows the son population number, and $y_m^{(i)}(j)$ shows each equalizer weight vector of the output signal of the individual by each path. Using the earlier formulas as the objective function of parallel genetic algorithms, and solving its minimum value, we obtain the best individual as the optimal weights coefficient of the adaptive algorithm. Due to the $J^{(i)}(f_m)>0$, therefore, the individual fitness functions are as follows:

$$Fit^{(i)}(m)=\frac{1}{J^{(i)}(f_m)} \qquad (13)$$

This paper uses the coarse-grained degree parallel genetic algorithm based on migration of ring topology, with each branch of the equalizer weight vector as a sub-population of the parallel genetic algorithm. Entering the parallel genetic algorithm, each sub-population is assigned to each processor's independent fitness calculation, selection, crossover, and mutation operations, and every generation of a ring topology operation on migration. Each sub-population has copies with the highest fitness individuals to adjacent sub-populations and replaces its lowest fitness of individuals; this can avoid algorithm premature convergence and can improve the convergence speed. Meeting termination conditions of the genetic algorithm, each branch of output signal after the equal-gain merger, we should input the rear equalizer, the equalizer weight vector by the adaptive algorithm adjustment based on orthogonal wavelet transform. This has played an important role in small range search and search speed. The orthogonal wavelet adaptive algorithm based on parallel genetic optimization and space diversity makes full use of the parallel genetic algorithm, space diversity, and orthogonal wavelet adaptive algorithms along with their respective advantages, and a better adaptive effect is obtained.