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The Analysis of Time Series Signals with Genetic Algorithms Involving Dynamic Bit Range Control for Genetic Operations

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***Abstract*:** Problems on multi objective optimization, time series prediction, the analysis of noisy observation data and the solution of implicit functions are all crucial in the consideration of real world issues. In this paper, we report the analysis for the characteristics of the time series periodic signals with genetic algorithms (GA) involving the dynamic range control for the genetic operations of GA. Subjects of this research have the same kinds of above problems. Analysis for the characteristics of the time series periodic signals means analyzing frequency components, the amplitudes and the phases of each frequency of the signals. As the time series prediction analysis is desired to converge as quickly as possible, we applied the dynamic bit range control for the genetic operations of GA. As the results of simulations, we could prove that GA has the applicability for the analyzing the characteristics of the noisy time series periodic signals and the dynamic bit range control for the genetic operations is effective for the early convergence of GA.

***Key words*:** Genetic algorithms, Dynamic bit control of genetic operations, Time series periodic signal analysis

I. INTRODUCTION

Researchers are already beginning to explore the applicability of evolutionary computation to the real world issues that contain the problems of multi objective optimization, time series prediction, the analysis of noisy observation data and the solution of implicit functions and so forth [1-8]. However, there are only a few examples of studies where evolutionary computation techniques have been applied to the issues that involve all of above problems at the same time. Some such examples are previous studies in which we reported about the effectiveness of genetic algorithms as a tool for tracking the moving object and the signal analysis (frequency components, amplitudes and phases) of the noisy time series periodic signals [9-15]. This paper is about the research on the analysis of the noisy time series periodic signals with GA involving the dynamic bit range control for the genetic operations. For the signal analysis, it is necessary to analyze the frequencies, amplitudes and the phases of each frequency. In many cases, Fast Fourier Transform (FFT) has been applied to the analysis of the time series periodic signal. However, if the period of the fundamental frequency of the time series periodic signals is unknown, FFT has the spectral leakage in its outputs in general [19]. Also, FFT needs the fitness valuation processing for its results because FFT does not have the valuation ability for its outputs. In this paper, we show that GA method of analysis can analyze the frequencies, amplitudes and phases concurrently without the spectral leakage and that the dynamic bit range control is effective for improving the settling time of the analysis.

II. FORMULATION OF THE ANALYSIS FOR THE TIME SERIES PERIODIC SIGNALS

Figure 1 shows the sound signal as a sample of the time series periodic signal $S(t)$. If the period of the signal in Fig.1 is T and the angular velocity is ω_0, the result of Fourier series expansion is expressed by (1) [18].

Equation (1) contains an integral expression that is not effective for computer processing. Figure 1 also shows the signal $S(n\Delta t)$ as quantum amplitude over an elapsed time. If Δt is the division interval of elapsed time and N is the division number of the period T. N is calculated as $T/\Delta t$. Equation (1) can be transformed into (2) which is a quantum expression after the transformation by Euler's formula on the condition that $n \geq N$. A_0 in (2) is the bias (direct current) component. A_1, A_2, A_3, $\cdots$, A_k, $\cdots$ are amplitudes of harmonic frequencies. f_p is the fundamental frequency. a_k and b_k are the coefficients of sine and cosine components of the k-th harmonic frequency. In the case of k = 1, symbols a_k, b_k and φ_k express the fundamental frequency component. In the case of $k \geq 2$, symbols a_k, b_k and φ_k express the k-th harmonic frequency components. If n is the order of the division, the quantum elapse time is expressed by $n\Delta t$ and the quantum amplitude of the signal is expressed by $S(n\Delta t)$, that is, the time series periodic signal is defined by f_p, A_0, a_1, b_1, a_2, b_2, $\cdots$, a_k, b_k, $\cdots$ of (2). Accordingly, the problem addressed in the signal analysis of GA, that is, analyzing the frequencies, amplitudes and phases of time series periodic signals can be formulated as an inverse problem involving complex implicit functions where it is necessary to find f_p, A_0, a_1, b_1, a_2, b_2, $\cdots$, a_k, b_k, $\cdots$ of the time series signal by working backwards from the sampled amplitude $S(n\Delta t)$. Harmonic frequencies, amplitudes and their phases are calculated by (2).

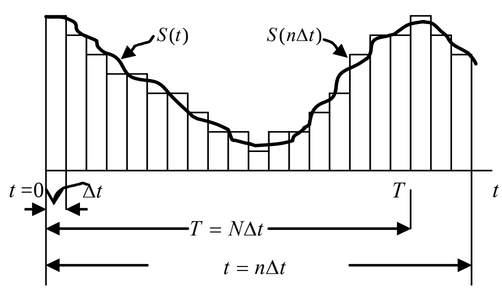

Fig.1. The time series sound signal $S(t)$ and Quantum expression of $S(n\Delta t)$ for the sound signal $S(t)$.

$$S(t) = \sum_{k=-\infty}^{\infty} C_k e^{ik\omega_0 t}, \tag{1}$$

where $C_k = \frac{1}{T}\int_0^T S(t) e^{ik\omega_0 t} dt$ and

$$k = -\infty, \cdots, -2, -1, 0, 1, 2, \cdots, \infty.$$

$$\begin{aligned} S(t) &= S(n\Delta t) \\ &= A_0 + A_1 \sin(2\pi f_p n\Delta t + \varphi_1) \\ &\quad + A_2 \sin(4\pi f_p n\Delta t + \varphi_2) \\ &\quad \cdots \\ &\quad + A_k \sin(2k\pi f_p n\Delta t + \varphi_k) \cdots, \end{aligned} \tag{2}$$

where $A_0 = \Delta t f_p \sum_{n=0}^{1/\Delta t f_p} S(n\Delta t),$

$$A_k = \sqrt{a_k^2 + b_k^2},$$

$$\varphi_k = \tan^{-1}\frac{a_k}{b_k} \text{ and}$$

$$k = 1, 2, 3, 4, \cdots.$$

III METHOD OF APPLING GA

1. Chromosome Coding Method

We assumed a sound signal propagated from unknown sound source located at a remote position in sea as the periodic time series signal. This sound is observed (sampled) by a observation equipment. Therefore, 600Hz is selected as the maximum value of the fundamental frequency f_p and 6 is selected as the maximum k because the higher frequency components of sound signals are absorbed in sea water [16]. In general, the larger k is, the smaller the amplitude of the time series periodic signal in sea is. Therefore, in the case of the individual of the sound signal analysis of GA, unknown components are f_p, A_0, a_1, b_1, a_2, b_2, ··· , a_6 and b_6. A_0 is dependent upon f_p as shown in (2) and can be analyzed concurrently with f_p as a dependent variable of f_p. Therefore, 13 chromosomes of f_p, a_1, b_1, a_2, b_2, ··· , a_6 and b_6 are set as the chromosomes that constitute the individual of the sound analysis of GA. The structure of the chromosome is that of a binary integer.

By assuming the maximum error being the composite observation error 0.1% and A/D conversion error 0.05%, of the weight of the LSB, that is, the resolution of f_p must be less than 0.11% for bit control in the genetic operations. Therefore, a bit length of f_p chromosome needs 14-bit integers. According to the same argument, a_k and b_k chromosomes need 14-bit integers.

2. Fitness Function

The fitness function for an individual I is given by (3). It is defined as the reciprocal of the sum of absolute value of the difference between the observed and estimated amplitude. The observed amplitude is obtained from the observation equipment at each elapsed time $n\Delta t$ from the observation equipment. The estimated amplitude is calculated corresponding to the elapsed time $n\Delta t$ based on estimated chromosomes esf_p, esa_1, esb_1, esa_2, esb_2, ··· , esa_6 and esb_6 for f_p, a_1, b_1, a_2, b_2, ··· , a_6 and b_6. m is the number of samplings and C is an appropriate constant. Denominator of (3) is linear with respect to the differences between observed amplitude and estimated amplitude. This fitness score has a relatively lower sensitivity than the denominator of sum of the square type or square root type. Lower sensitive fitness function is adaptive for this analysis because there are many deceptive solutions [17].

$$F_b(I) = C \times m \Big/ \sum_{n=0}^{m-1} \left| esS(n\Delta t) - oS(n\Delta t) \right| \tag{3}$$

3. Genetic Operation

A. Exploration (*wide area searching*)

The method for selecting the individuals carried forward to the next generation from the current generation is shown in Fig.2. All individual (the total number of chromosomes) P sent from the previous generation is evaluated by calculation of fitness and sorted in descending order. We retain a fixed proportion E as elite from the highest fitness individual and send them to next generation unconditionally, and the number of M (=P – E) discarded individuals are supplemented by roulette selection to preserve the original population P. Making up of the deficit for M is done as follows. One pair of individual is chosen as parent by roulette selection from all individual P of the current generation.

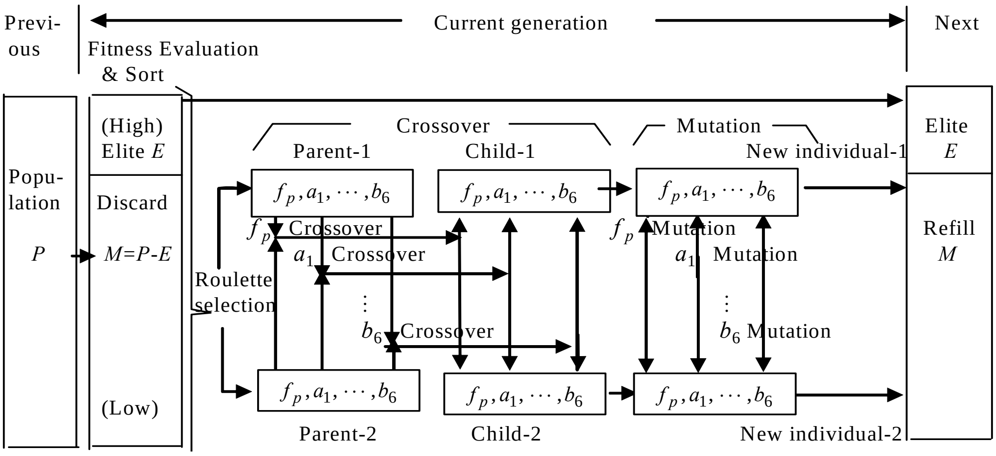

Figure.2. Flowchart of genetic operation. One pair of chromosome is selected by roulette selection, and crossover and mutation are done for each chromosome respectively and one pair of the new chromosome is produced.

The chromosomes f_p, a_1, b_1, ···, a_6, b_6 of this one pair of individual is then subjected to one-point crossover between each of the same kind of chromosomes independently (that is. crossover between f_p and f_p, a_1 and a_1,…., b_6 and b_6 of both individual) to produce one pair of child individual. After crossover operation, all chromosome of produced one pair child individual is subjected to mutation independently. Through the crossover and mutation processes, one pair of new individual is produced and carried forward to the next generation. Above processes are repeated until the making up of the deficit for M is completed (M/2 times). In preliminary trials we found three phenomena. The first of those phenomena is that sub chromosome f_p starts to converge earlier than the other chromosomes. So in the exact simulation, we selected different (reduced) mutation rate for f_p from the other sub chromosomes. The second phenomenon is that the solution starts to converge around the 10th generation, so for subsequent generations we reduced the mutation rate for all chromosomes. We did those to avoid destroying the chromosome that had already approached convergence. In the exact simulation, the mutation rate is changed from the 20th generation onwards. The third phenomenon is as follows. From the 10th generation onwards, new type individuals that are calculated from the fittest individual of the current generation are effective for the earlier convergence. These new type individuals consist of chromosomes that are modified the chromosomes of the fittest individual of the current generation as much as 2% uniform random numbers of the chromosome in the fittest individual.

B. Exploitation (local area searching)

We have already reported about the research on the analysis for the noisy periodic time series signals [11]. As the previous research had only the exploration (wide area searching) in it, it required many generations for settling to desired accuracy. We recognized that it needed any exploitation (local area searching). In this research, we applied the dynamic bit range control for the genetic operations as the local area searching. The purpose of the local area searching is to shorten the settling generations of GA analysis. Figure 3 shows the relationship between the wide area searching (non-dynamic bit range control), local area searching (dynamic bit range control) and generations. The processing for the three phenomena described in the wide area searching is applied here also. Switching generation from wide to local is done according to the fitness build up conditions.

$$B_{cr} = (B_{max} - B_{min}) \times (1.0 - F_{bc}/F_{max}) + B_{min} \qquad (4)$$

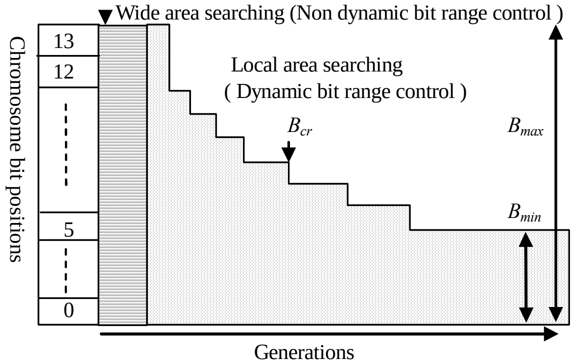

Fig.3. The dynamic bit range control for the genetic operations

Bit control range is calculated by (4). In (4), B_{cr} is the bit control range, B_{max} is full bit range of each chromosome, B_{min} is the minimum bit range, F_{bc} is the best fitness of the latest generation and F_{max} is the maximum fitness selected by the preliminary trials. We selected 6 bits as B_{min} by the preliminary trials.

IV. EVALUATION METHOD

1. Evaluation System

Figure 4 shows the concept of the evaluation system applied to this analysis. This system consists of a Sound Generator and a Sound Analysis GA that is structured by an Estimate Sound Generator and a Sound Evaluator. The parameters of GA analysis are given in Table 1.

Table 1. Parameters of GA applied to this analysis.

Parameter	Value	
Population	3000	
Elite number	60	
Max gene	50	
Crossover	0.8/pair of chromosome	
Mutation	generation <20 0.0001/bit f_p 0.0005/bit a_k, b_k	generation ≥ 20 0.00005/bit f_p 0.0001/bit a_k, b_k
Sample Freq	6.1(Nyquist), ···, 12.2kHz	

2. Results of the Evaluation

Table 2 shows the errors in the harmonic frequencies, levels and phases of a sample of the sound characteristics. The error of fundamental frequency is 0.063%. The phase error corresponding to the fundamental frequency is 0.061 deg. Little difference errors among the sampling frequency are detected.

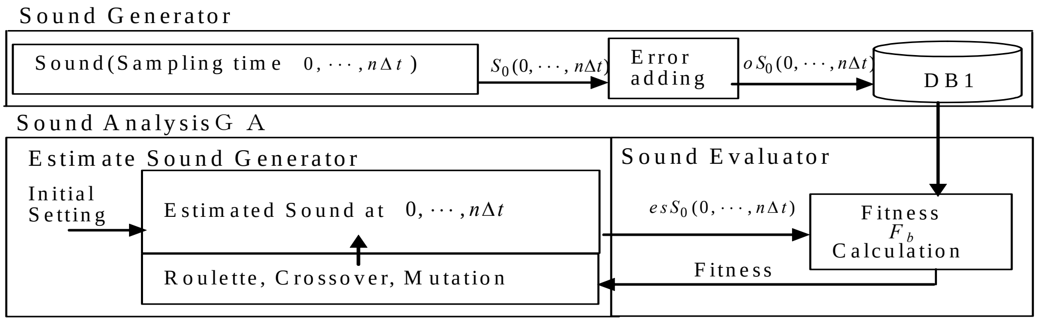

Fig.4. The flowchart of GA evaluation system. The GA evaluation system consists of a Sound Generator and a Sound Analysis GA that is structured by an Estimate Sound Generator and a Sound Evaluator.

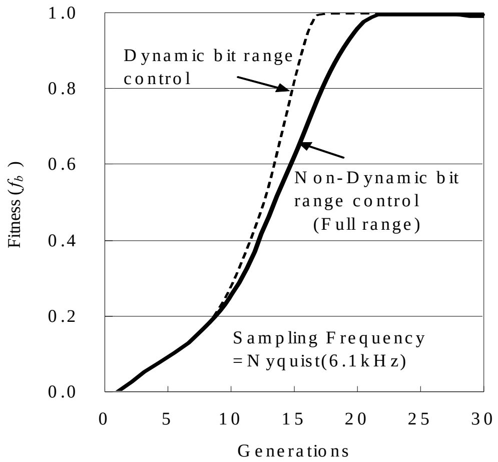

Fig.5. The relationship between the best fitness score of dynamic bit range control, non dynamic and generations.

Table 2. The accuracy of frequencies, levels and phases of a sample of the sound characteristics.

True				Error	
Observed Freq	Level		Phase	Level	Phase
Hz	a	b	rad	$\times 10^{-4}$	deg
Bias:A_0	0.50	–	–	1.60	–
1st: 502.52	1.00	1.00	$\pi/4$	4.22	0.040
2nd1005.04	0.70	-0.70	$7\pi/8$	7.12	0.042
3rd:1507.56	-0.40	-0.40	$5\pi/4$	4.04	0.054
4th:2010.08	-0.20	0.20	$3\pi/4$	4.32	0.044
5th:2512.60	0.10	0.10	$\pi/4$	5.08	0.064
6th:3015.11	-0.03	0.03	$3\pi/4$	6.50	0.100
Level Avg Error(for 1st)				0.061%	
Freq Avg Error(for 1st)				0.062Hz	
Phase Avg Error(for 1st)				0.059deg	

Figure 5 shows the relationship between the best fitness of the dynamic bit range control, non-dynamic bit control and generations. The fitness f_b on the vertical axis is normalized by $f_b = 1.0 - 1.0 / \{1.0 + F_b(I)\}$ from $F_b(I)$ of (3). Settling of the best fitness for the wide area searching is improved around 10+% by taking into account the three phenomena described in 3.3.1. By the local area searching following after the wide area searching, settling of the generations is improved around 25%.

V. CONCLUSION

Time series prediction analysis is one of the major problems in real world issues and this analysis is required to settle as quickly as possible. Through the computer simulations, we could prove the applicability of GA to the analysis for the noisy periodic time series signal that is one of the time series prediction. Also, we could prove the effectiveness of a technique of the dynamic bit range control for genetic operations for reducing the settling generation of GA. By this technique, the crossover and mutation area slide from the wide area searching to the local area searching along to the generations. We will continue to research on the searching techniques for GA.

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