Parameters Estimation of Ultrasonics Echoes using the Cuckoo Search and Adaptive Cuckoo Search Algorithms

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***Abstract*—In this study we present a novel approach to estimate ultrasonic echo pattern using the two algorithms: *Cuckoo Search* (CS) and *Adaptive Cuckoo Search* (ACS). We model ultrasonic backscattered echoes in terms of superimposed Gaussian echoes corrupted by noise. Each Gaussian echo in the model is a non linear function of a set of parameters: echo bandwidth, arrival time, center frequency, amplitude and phase. The estimation of parameters is formulated as a nonlinear optimisation problem. Simulations are carried out to assess the performance of the proposed algorithms. Finally the algorithms were applied on experimental data for thickness measurement. The CS algorithm converges to best solution with less time than ACS. However, ACS algorithm outperforms CS.**

***Keywords*—cuckoo search algorithm; echo parameter estimation; ultrasonic signal; thikness measurement**

I. Introduction

In ultrasonic Non Destructive Evaluation (NDE) applications, the pattern of ultrasound echo signal reveals important physical information such as the location, size and orientation of defects, as well as attenuation and dispersion characteristics of the propagation path. It has been shown that model-based signal analysis is robust in echo evaluation and parameter estimation [1-2], especially when the adopted model has parameters strongly pertinent to the physical information of reflectors in material and structures. Estimated parameters of echoes can be used to quantitatively evaluate structures and characterize material. Nevertheless, signal processing and analysis is still challenging due to the non-stationary nature of ultrasound NDE signals.

The ultrasonic backscattered echo from a flat surface reflector can be written as [1]:

$$y\left(t\right)=s\left(\theta;t\right)+v\left(t\right) \tag{1}$$

Here, $s(\theta;t)$ is a Gaussian echo model, and

$$s(\theta;t)=\beta e^{-\alpha(t-\tau)^2}\cos\left(2\pi f_c\left(t-\tau\right)+\varphi\right) \tag{2}$$

$$\theta=\left[\alpha\ \ \tau\ \ f_c\ \ \varphi\ \ \beta\right].$$

α is bandwidth factor that determines the bandwidth of the echo or the pulse duration in the time domain; τ is arrival time, indicates the location of the reflector; f_c is center frequency, governed by the transducer center frequency; φ is phase and β is amplitude. $v(t)$ is the additive white Gaussian noise (WGN) process. Equation (3) is an altered version to describe the multiple echoes from the reflector [1],

$$y\left(t\right)=\sum_{m=1}^{M} s(\theta_m;t)+v\left(t\right) \tag{3}$$

Here, M denotes the number of superimposed Gaussian echoes; echo vector θ_m indicates the shape and position of each echo. The summation term represents a signal model of multiple reflections while the number of reflections is unknown. In order to estimate M, we can use the information theoretic criteria such us the minimum description length (MDL) [3].

Cuckoo search is a metaheuristic search algorithm which has been proposed by Yang and Deb [4]. The algorithm is inspired by the reproduction strategy of cuckoos. At the most basic level, cuckoos lay their eggs in the nests of other host birds which may be of different species. The host bird may discover that the eggs are not its own and either destroy the eggs or abandon the nest all to gather. This has resulted in the evolution of cuckoo eggs which mimic the eggs of local host birds [5]. To apply this as an optimization tool, Yang and Deb [4] used three idealized rules: (i) Each cuckoo lays one egg, which represents a set of solution co-ordinates at a time and dumps it in a random nest; (ii) A fraction of the nests containing the best eggs, or solution, will carry over to the nest generation; (iii) The number of the nests is fixed and there is a probability that a host can discover an alien egg. If this happens, the host can either discard the egg or the nest and this result in building a new nest in a new location. The CS algorithm has been applied successfully to variety of optimization problems [6-7]. In this study, we propose to apply the CS and ACS algorithms for the estimation of ultrasonic echoes parameters. The performances of these algorithms is tested and compared with simulated and experimental ultrasonic echoes.

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The remainder of this paper is organized as follows. The CS and ACS algorithms are presented respectively in Section II and Section III. Section IV addresses the application of these algorithms on a simulated ultrasonic signal. Section V presents experimental results. Section VI concludes the paper.

II. CUCKOO SEARCH (CS) ALGORITHM

The Cuckoo search (CS) algorithm was developed by the Yang & Deb [4] inspired by social thinking of the Cuckoo birds. The Cuckoo bird lays its eggs laid by Cuckoo with a probability $p_a \in [0, 1]$. The eggs were discovered by the host birds either through the eggs or while the abandonment of nests to build a new one [8]. For simplicity of mathematical modeling, the number of host nests is assumed to be fixed. The mathematical model of CS algorithm was described as [9]:

Assume in the environment, there is N Cuckoos present, where each Cuckoo represents a nest. The nest relates to the solution of an optimization problem. Let us initialize the search space of n dimension for ith Cuckoo as $X_i = (x_i^1, \ldots, x_i^d, \ldots, x_i^n)$ for i=1,2,...,N. Then at the time l, the new search space $X_i(l+1)$ for ith Cuckoo will be calculated as

$$X_i(l+1) = X_i(l) + \eta \times Levy(\gamma) \tag{4}$$

Where η is constant parameter related to dimension of search space helps in deciding the step size, and $Levy(\gamma)$ is the random walk through a *Levy* flight [10]. In most cases η is taken as a constant value equal to 1.

In general, a random walk of next location only depends on the current location as derived from Markov chain and the *Levy* step. In long run, the *Levy* step gives larger step while exploring search space. Generally, the *Levy* step is taken from the *Levy* distribution. Most commonly, the *Levy* distribution is obtained from the Mantegna algorithm. So the *Levy* step size can be obtained from the Mantegna algorithm as

$$Levy(\gamma) = \frac{u}{|z|^{\frac{1}{(\gamma-1)}}}, \tag{5}$$

where u and z are obtained from a normal distribution, γ is considered in the range [1,3], and the standard deviation related to normal distribution is

$$\sigma_u(\gamma) = \left(\frac{\Gamma(1+\gamma).\sin\left(\frac{\pi\gamma}{2}\right)}{\Gamma\left(\frac{1+\gamma}{2}\right).\gamma.2^{(\gamma-1/2)}} \right)^{\frac{1}{\gamma}}, \text{ and } \sigma_z(\gamma) = 1. \tag{6}$$

Finally, $Levy(\gamma)$ multiplied with a factor χ gives step size. The value χ is generally chosen such that the *Levy* step should not be aggressive. Conceptually, *Levy* distribution for large steps applied a power law, thus an infinite variance depicted as

$$Levy(\gamma) \sim u = l^{-1} \tag{7}$$

III. ADAPTIVE CUCKOO SEARCH (ACS)

The CS algorithm is heuristic search algorithm which generally explores the search using the *Levy* step. The *Levy* step is taken from the *Levy* distribution given by either Mantegna algorithm or McCulloch's algorithm. In [11], the author suggested that *Levy* distribution using McCulloch's algorithm is potent than the Mantegna's algorithm. Anyway, in the CS algorithm follow the *Levy* distribution. We present an adaptive Cuckoo search description without using *Levy* distribution [9].

The standard CS algorithm does not have any control over the step size in the iteration process to reach global minima or maxima. We incorporate the step size to the fitness of the individual nest in the search space and the current generation. On the other hand, in some literature η has been taken as a fixed parameter, here we omit the η parameter. Then the adaptive CS algorithm step can modelled as

$$step_i(l+1) = \left(\frac{1}{l}\right)^{\left|\frac{bestfit(l) - fit_i(l)}{bestfit(l) - worstfit(l)}\right|}, \tag{8}$$

where
l = Generation of Cuckoo search.
$fit_i(l)$ = Fitness value of ith nest generation.
$bestfit(l)$ = Best fitness value in tth generation.
$worstfit(l)$ = Worst fitness value in tth generation.

The step size initially high, but when the generation increases the step size decreases. That indicates when the algorithm reaches to the global optimal solution step size is small. From the Eq. (8), it clearly indicates that the step size adaptively decides from the fitness value. Then the adaptive CS algorithm (ACS) is modelled:

$$X_i(l+1) = X_i(l) + randn \times step_i(l+1) \tag{9}$$

The Eq. (9) gives leads to new search space for ACS algorithm from the current solution. Another advantage of the ACS is, it does not require any initial parameter to be defined.

IV. SIMULATED RESULTS

To study the CS and ACS algorithms performance, we tested them on superimposed ultrasonic echoes with additive WGN. The signal is made up of two echoes.

For simulation, two ultrasonic Gaussian echoes (2) are simulated in terms of bandwidth factor α (MHz)^2, arrival time τ (µs), center frequency f_c (MHz), phase φ (rad), and amplitude β. The signal is shown in Fig.1. (a). These echoes are sampled at the sampling frequency f_s = 200 MHz. A zero mean WGN is added to this signal [1] with variance corresponding to a signal to noise ratio (SNR) of 12,5 dB. The actual parameters used in the simulation are listed in Table I. Then, the CS and ACS algorithms are applied to estimate the echoes parameters. For the algorithms setup, the number of nest N is 100, p_a = 0,25 and the maximum number of generation is 5000.

TABLE I. PARAMETER ESTIMATION RESULTS FOR TWO ECHOES WITH SNR OF 12.5 DB USING CS AND ACS ALGORITHMS

First echo		β	$\alpha\,(\mathrm{MHz})^2$	$\tau\,(\mu\mathrm{s})$	$f\,(\mathrm{MHz})$	$\varphi\,(\mathrm{rad})$
		1	**15**	**1**	**8**	**0,52**
Best	**CS**	1,0306	15,9865	1,0094	8,0028	0,9875
	ACS	1,0180	15,5517	1,0171	8,0001	1,3721
Mean	**CS**	0,8626	16,2208	1,3054	7,3435	2,6799
	ACS	0,8557	17,0871	1,3601	7,1871	2,1576
Std.	**CS**	0,3669	10,6575	0,8223	1,7766	2,3032
	ACS	0,3828	11,7655	1,0643	2,0566	2,0562

Second echo		β	$\alpha\,(\mathrm{MHz})^2$	$\tau\,(\mu\mathrm{s})$	$f\,(\mathrm{MHz})$	$\varphi\,(\mathrm{rad})$
		0,9	**12**	**2,5**	**7,5**	**1,04**
Best	**CS**	0,9228	12,3574	2,4978	7,5273	0,9347
	ACS	0,9286	12,7421	2,4948	7,5318	0,7935
Mean	**CS**	0,9394	19,4122	2,6740	6,9377	2,5917
	ACS	0,9801	17,9873	3,0242	6,7341	2,7099
Std.	**CS**	0,3813	15,5528	1,0121	2,1400	2,2533
	ACS	0,4269	14,7525	1,2337	2,3609	2,2731

In order to convert the parameter estimation problem into optimization problem, the following objective fitness function is defined [12]:

$$F = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left(y - \hat{y}\right)^2}\,, \tag{10}$$

where $i = 1, 2, \ldots, T$ is the sampling time point and T denotes the length of data. For comparison, we use best estimate ('Best'), mean ('Mean') and standard deviation ('Std') to get the best results which are shown in Table I. The estimated echoes are plotted in Fig. 1 (b) and Fig. 1 (c) respectively with CS and ACS algorithms.

The parameters estimation tabulated in Table I, is robust, regardless of a significant noise level and echo time location.

V. EXPERIMENTS

In this study, the CS and ACS algorithms have been tested on the experimental data. In the ultrasonic NDE applications, the useful parameters of interest are β, τ and f_c [13].

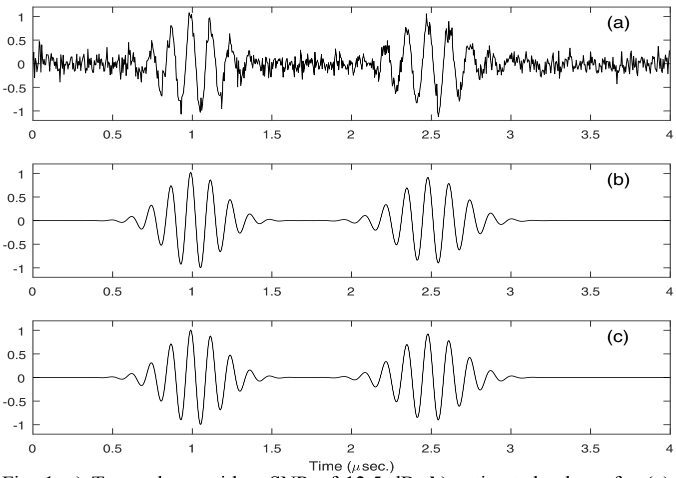

Fig. 1. **a)** Two echoes with a SNR of 12.5 dB; **b)** estimated echoes for **(a)** with CS algorithm; **c)** estimated echoes for **(a)** with ACS algorithm

The sample used is a carbon fiber-reinforced polymer multi-layered composite material (CFRP) achieved with two delamination defects located at front surface and back wall [13]. Delaminations in thin composite laminates are usually detectable by an immersion transducer operating in pulse-echo mode. Fig. 2 shows a typical ultrasonic setup. Multiple waves are reflected from the surfaces of the specimen as well as from delaminations, as shown in Fig. 3.

Fig. 4 (a) shows closely-spaced echoes between delamination and front surface echo. τ_d represents the defect echo location of the delamination zone, τ_{FS} represents the time location of the front surface echo and τ_B represents the time location of the ultrasonic first back wall echo of the sample. The delamination depth in the material can be given by using Eq. (11):

$$d = \frac{1}{2}\left[V_{sample}\left(\tau_d - \tau_{FS}\right)\right], \tag{11}$$

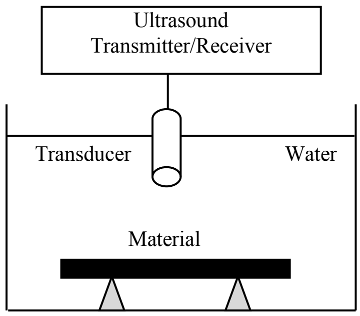

Fig. 2. Experimental setup for immersion pulse-echo testing

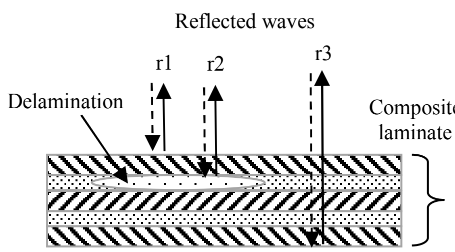

Fig. 3. Reflected echoes

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TABLE II. THIKNESS OF THE PART AND DEPTH OF DEFECT

Signal		τ_{FS} (µs)	τ_d (µs)	τ_B (µs)	*Thickness of the part (mm)*	*Position of the delamination (mm)*
Actual parameters		–	–	–	**3.3**	**0.63**
Best	**CS**	3,32	3,69	5,68	**3,34**	**0,52**
	ACS	3,32	3,77	5,68	**3,34**	**0,64**
Mean	**CS**	2,89	3,74	5,42	3,59	1,21
	ACS	3,04	3,68	5,11	2,92	0,90
Std.	**CS**	0,99	0,88	1,44	1,70	1,66
	ACS	0,76	0,63	1,22	1,47	1,29

where V_{sample} = 2830 m/s is the velocity of sound in the material [13]. The data are obtained using a transducer centered at 2.25 MHz. A thickness of CFRP is 3.3 mm [13]. Fig. 4 (b) and Fig. 4 (c) show the estimated echoes by respectively the CS and ACS algorithms using M = 3, the number of nest is 100, p_a = 0,25 and the number of generation is 100000. Parameter estimated results are listed in Table II. The convergence curves are shown in Fig. 5.

The results show that both CS and ACS algorithms are robust and reliable for estimating the thickness of the part. The CS algorithm converges rapidly to the global solution, whereas ACS converges slowly but provides an accurate estimate of the position of the delamination.

VI. CONCLUSION

In this paper, we present a new method for the estimation of superimposed Gaussian ultrasonic echoes parameters using the two algorithms: Cuckoo search and Adaptive Cuckoo search. The obtained results have a good accuracy, and the performances are almost independent of the noise. The CS and ACS algorithms show a high robustness and reliability in the parameters estimation. The ACS has better convergence than CS in term of estimation precision.

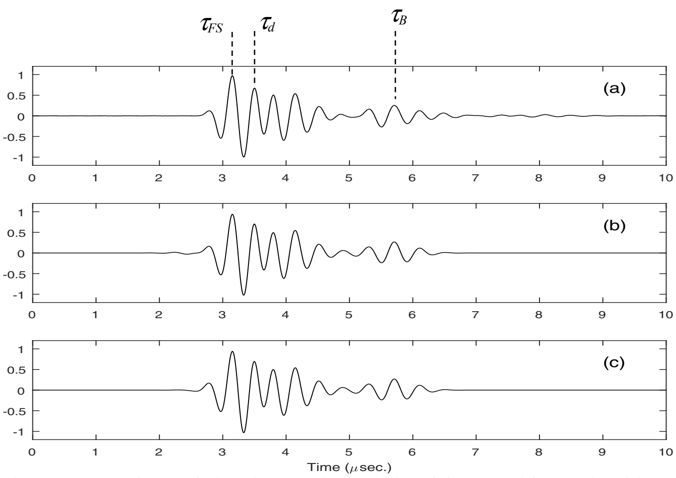

Fig. 4. **a)** Experimental signal; **b)** Estimated signal for **(a)** with CS algorithm; **c)** Estimated signal for **(a)** with ACS algorithm

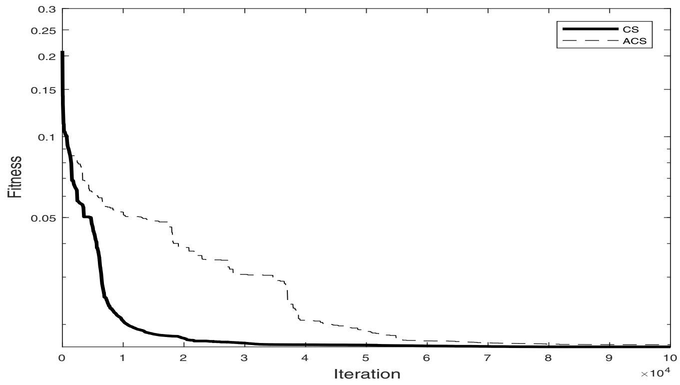

Fig. 5. Performance comparison

REFERENCES

[1] R. Demirli, and J. Saniie, " Model-based estimation of ultrasonic echoes. Part I: analysis and algorithms," IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, vol. 48, pp. 787-802, May 2001.

[2] R. Demirli, and J. Saniie, " Model-based estimation of ultrasonic echoes. Part II: nondestructive evaluation applications," IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, vol. 48, pp. 803-811, May 2001.

[3] M.Wax and I. Ziskind, "Detection of the number of coherent signals by the MDL principle," IEEE Trans.A coust.Sp eech Signal Processing, vol. 37, no. 8, pp. 1190–1196, Aug. 1989.

[4] X. S. Yang, & S. Deb, Cuckoo search via Lévy flights. Proceedings of World Congress on Nature & Biologically Inspired Computing (NaBIC 2009, India), IEEE Publications, USA 2009; p. 210-214.

[5] S. Walton, O. Hassan, K. Morgan, M.R. Brown, Modified cuckoo search: a new gradient free optimization algorithm, Chaos, Solitons & Fractals, Vol 44, pp. 710-718, 2011.

[6] I. H. Gandomi, X. S. Yang & A. H. Alavi, Cuckoo search algorithm: a metaheuristic approach to solve structural optimization problems. Engineering with Computers, 29(1), pp. 17-35. 2013

[7] X. S. Yang, & S. Deb, Engineering optimization by cuckoo search. International Journal of Mathematical Modeling and Numerical Optimisation,1(4), pp. 330-343, 2010.

[8] S. Chakraverty, and A. Kumar, ''Design optimization for reliable emgedded system using Cuckoo search,'' Proc. International Conference on Electronics, Computer Technology, vol. 1, pp. 164-268, 2011.

[9] M. Naik, MR Nath, A, Wunnava, S. Sahany and R. Panda ''A new Adaptive Cuckoo Search Algorithm, '' IEEE 2nd International Conference on Recent Trends in Information Systems (ReTIS), 2015, pp. 1-5.

[10] P. Barthelemy, J. Bertolotti, and D. S. Wiersma, ''A Lévy flight for light,'' Nature, vol. 453, pp. 495-498, 2008.

[11] H. Soneji, and R. C. Sanghvi, ''Towards the improvements of Cuckoo search algorithm,'' Information and Communication Technologies (WICT), 2012 World Congress on, pp. 878-883.

[12] J.Wang, B. Zhou and S. Zhou, "An Improved Cuckoo Search Optimization Algorithm for the Problem of Chaotic Systems Parameter Estimation," Computational Intelligence and Neuroscience, Vol. 2016 (2016), pp. 1-8.

[13] A. Benammar, R. Drai and A. Guessoum "Detection of delamination defects in CFRP materials using ultrasonic signal processing," Ultrasonics 48 (2008) 731–738.