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Research on Ultrasonic CT Imaging of Concrete Materials Based on Simulated Annealing Particle Swarm Algorithm

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Abstract: In ultrasonic computerized tomography imaging of concrete structures, Particle Swarm Optimization (PSO) algorithm may produce premature and lead to poor imaging results which always can not meet requirement. An improved PSO inverse algorithm based on Simulated Annealing (SA) algorithm is presented here. The imaging accuracy can be enhanced by combining the PSO and SA algorithm which can take advantage of the ability of jumping out of the local optima in SA and keep the capacity of smart and global search in PSO. Numerical simulation demonstrates that higher imaging quality is obtained and the embedded object is clearer.

Key words: Concrete materials, ultrasonic CT, SA algorithm, PSO algorithm

INTRODUCTION

In civil engineering, concrete is one of the main structural material of the building. It is a non-uniform porous changing anisotropic composite. Both industrial and civil construction, or highway, railway, water conservancy and hydropower project have extensive use of concrete materials (Hosseini *et al*., 2008; Li *et al*., 2008). Due to a variety of defects (such as voids, silted, etc.) often appear in the construction process and thus affect the durability of the whole structure and even affect the safety of the use of the entire building. Therefore, how to strengthen the monitoring and control of the quality of concrete, has become one of the hot of research in building technology today (Yamada and Miyakoshi, 2008; Zhu *et al*., 2008).

Due to the objective reasons of concrete structural characteristics and environment, conventional NDT methods are subject to varying degrees of restrictions, unable to meet the needs of concrete structure detection (Lin, 2002; Shen *et al*., 2000). Ultrasound tomography technology is a remarkable new technology and it is formed by conventional ultrasonic testing methods combined with ray CT technology. It has an important position in the modern industrial non-destructive testing, has become an important means of the structure quantitative detection (Chang *et al*., 2010). Currently, ultrasound tomography includes forward modeling and inversion of the two basic calculations. Forward is the base of inversion and its model selection and solution accuracy directly affect the inversion accuracy. According to the characteristics of ultrasonic wave propagation in concrete, curved ray tracing and some of their improved method are more mature, tracking the propagation path of the ultrasonic well; Inversion process is actually a process of optimization problems, important aspects affecting the image quality directly determines the validity of the results, the focus of the current study. The inversion algorithm is the direction of development (eg, SVD, BPT, ART, SIRT method) from linear to nonlinear (such as the echelon method, fuzzy neural network algorithm and genetic algorithm methods). Certain practical effects are obtained for some of the existing inversion method in some respects but the stability and accuracy of the result of imaging is still very difficult to meet the actual requirements (Li *et al*., 2012; Chang *et al*., 2010; Das and Bhattacharya, 2011).

Particle Swarm Optimization (PSO) algorithm by Kennedy and Eberhart (1995) is a evolutionary computation techniques of global optimization capability based on swarm intelligence (Kennedy and Eberhart, 1995). This optimization algorithm is simple, easy to implement and profound intelligence background, particularly suitable for engineering applications and is now widely used in function optimization, neural networks, pattern classification, fuzzy system control and other applications (Das and Bhattacharya, 2011; Chiu *et al*., 2011). However, with other intelligent

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optimization algorithms, particle swarm optimization algorithm is also has a great shortage, such as easy to fall into local extreme point, slow convergence speed in the later stage of evolution, optimization of poor accuracy, etc. To overcome these shortcomings, this study presents a Simulated Annealing Particle Swarm (SA-PSO) algorithm, Simulated Annealing (SA) algorithm is embedded into the particle swarm optimization algorithm, using strong pop partial solution of simulated annealing algorithm, to avoid particle swarm optimization algorithm into local extremum point and to improve the convergence speed and accuracy of the algorithm at the later stage of evolution and the SA into a parallel algorithm (Sharma *et al*., 2009; Zhu and Ye, 2009).

IMPROVED ALGORITHM PRINCIPLE

Particle swarm algorithm: For a solution vector in the R-dimensional space it can be regarded as one particle in this space while the particles given two additional properties: (1) R-dimensional vector represents the particle position; (2) R-dimensional vector represents the particle velocity. For example, particle swarm containing N particles is in D-dimensional solution space, position and velocity of the including any of the i-th particles, respectively, expressed as $X' = (x_{i,1}, x_{i,2}...x_{i,d})$ and $V = (v_{i,1}, v_{i,2}...v_{i,d})$. In iterative process, the particles update themselves by tracking the optimal solution for itself and the whole group. The individuals optimal solution is expressed as $p_g = (p_{i,1}, p_{i,2}...p_{i,d})$. Overall optimal solution is expressed as $p_g = (p_{g,1}, p_{g,2}...p_{g,d})$. The formula of update position and velocity of particle in iterative optimization process is as follows:

$$\begin{aligned} & v_{i,j}(t+1) = wv_{i,j}(t) + c_1 r_1 [p_{i,j} - x_{i,j}(t)] + c_2 r_2 [p_{g,j} - x_{i,j}(g)] \\ & x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1), j = 1, 2, \cdots, d \end{aligned} \quad (1)$$

where, in i = 1, 2, ...N, d = 1,2,...D, w is inertia weight factor. C_1 and C_2 are a positive learning factor. R_1 and R_2 are uniformly distributed random numbers between 0-1. The performance of particle swarm algorithm depends largely on the control parameters of the algorithm and select the parameters generally follow the principle:

- **The number of particles:** The selection of the number of particles depends on the complexity. In general, the principles of selecting number of the number of particles is : simple questions take 20, particularly complex issues to take more than 100 and other issues take between 20-100
- **Particle dimension:** Depending on the problem, the study is according to the number of pixels
- **Particles range:** Depending on the problem, this study based on the range of ultrasound propagation velocity in concrete
- **Maximum speed V_{max}:** Decided by the maximum distance of the particle movement in a complete iteration
- **Learning factor:** Learning factor reflects the particle's ability to self-learning and to learn from the best individual in the population and its range is [0, 4], usually taken c_1 and c_2 for 2
- **Inertia weight:** Determine the proportion of particles inherit their own speed and optimal particle velocity

When the particle searching in the space ,they update their own and group information to determine the speed and direction that moving to the target.

Simulated annealing algorithm: The simulated annealing algorithm is random optimization algorithm based on the Monte Carlo iterative solution strategy. Algorithm is set at a higher temperature, this temperature satisfy all possible solutions of the solution space. Then according to certain rules of cooling combined with the overall acceptance probability function for solving. Algorithm during optimization, first determine an initial temperature. This temperature is sufficient to allow any solution can accept. Study objective function value and input a disturbance for the current state. Then calculate the objective function value in case of disturbance exists. Accept a good point with probability 1 and receiving poor points of a condition set in advance, until the system was cooled. As it can be in some form of probability to accept less point, avoids solving process into a local solving. Probability expression based on the Metropolis criterion of simulated annealing algorithm is as follows:

$$P_r(i \Rightarrow i+1) = \begin{cases} 1 & f(i+1) \le f(i) \\ \exp(\dfrac{f(i) - f(i+1)}{t}) & f(i+1) > f(i) \end{cases} \quad (2)$$

where, in f(x) and f((x+1), respectively, for the objective function before and after the disturbance.

SA-PSO algorithm principle: In order to overcome the shortcomings that the particle swarm optimization algorithm is easy to fall into local extreme points and lead to precocious and slow convergence and poor accuracy of later stage of evolution. Simulated annealing algorithm is introduced into the particle swarm algorithm and using the simulated annealing algorithm has strong ability to jump out of local optimization, get more satisfactory results, described in the specific algorithm is as follows:

- A solution vector of random initialization and ultrasonic propagation path is calculated according to the solution vector
- The position and velocity of each of the particles remaining in the populations is of random initialization
- Calculate the fitness of each particle and store the position and fitness value of each particle in this iteration in Pi and store location and fitness of the individual which has the best fitness value among all optimal particle in P_g
- Determine the initial temperature
- Calculate the fit value of Pi under the current temperature in accordance with the following formula:

$$TF(p_i) = \frac{e^{-(f(p_i)-f(p_g))/t}}{\sum_{i=1}^{N} e^{-(f(p_i)-f(p_g))/t}} \quad (3)$$

- Using roulette strategy to determine an alternative value P_g of global optimal from all Pi. And then update the speed and position of each particle according to the following formula:

$$\begin{aligned} v_{i,j}(t+1) &= \varphi[v_{i,j}(t) + c_1 r_1 [p_{i,j} - x_{i,j}(t)] + c_2 r_2 [p_g' - x_{i,j}(t)]] \\ x_{i,j}(t+1) &= x_{i,j}(t) + v_{i,j}(t+1) \end{aligned} \quad (4)$$

Where:

$$\varphi = \frac{2}{\left|2 - C - \sqrt{C^2 - 4C}\right|}, C = c_1 + c_2$$

- Calculate the new target value of each particle and update the value of Pi of all particles and groups P_g value
- Annealing operation
- If the stop condition (the defaulted number of iterations of computation accuracy) is met, the search stops, outputting the result, otherwise go to step (4)
- To determine whether the adjacent path error twice to meet the accuracy,if the error meet the accuracy and then ending the algorithm, otherwise it go to step (2).

Initial temperature and annealing method have a certain influence in algorithm. Algorithm uses the following initial temperature and annealing:

$$t_{k+1} = \lambda t_k, t_0 = f(p_g)/\ln 5 \quad (5)$$

NUMERICAL SIMULATION

Finite element model: Concrete structure model building by using finite element software is shown in Fig. 1. The portion marked A in the Figure is the low speed area, B labeled part of the high-speed zone, A and B for the areas of concrete. The velocity of sound in the various regions of the model can be calculated in accordance with the equation (6). Material parameter values of the various regions of the model are listed in Table 1 and sound velocity of the various regions were calculated according to the material parameters. Sound velocity of concrete regional is 3892.7 m sec^{-1}, high-speed zone 4175.3 m sec^{-1} and the low-speed zone 3388.1 m sec^{-1}.

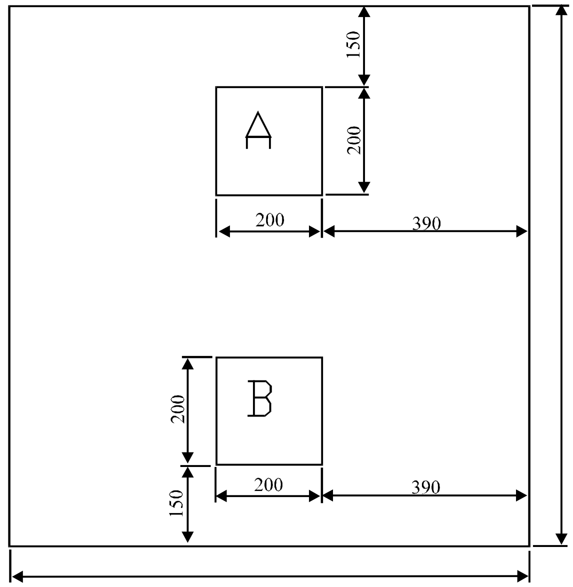

Fig. 1: FEM model of the concrete structure

Table 1: Material parameter values of the model

Model zone	Density ($kg\ m^{-3}$)	Young's modulus (Mpa)	Poisson's ratio
Concrete	2600	35000	0.21
High-speed zone	3000	32000	0.28
Low-speed zone	2100	20000	0.19

$$v = \sqrt{\frac{E}{\rho}} \cdot \sqrt{\frac{(1-\delta)}{(1+\delta)(1-2\delta)}} \quad (6)$$

Test program and simulation signal test: Simulation test program is shown in Fig. 2. The ultrasonic signal was launched in the left side of the concrete structure. From top to bottom, set nine incentives to launch successively. Signal receiving in the right, also arranged nine receiving position, test a total of 81 travel time data. Fig. 3 is the simulation snapshot of the wave field which the fifth launch position issued ultrasound signal.

Before performing chromatography, the model test program is divided into 9×9 pixel unit, make the test data in accordance with the classic curved ray tracing method for forward computation to get acoustic propagation path.

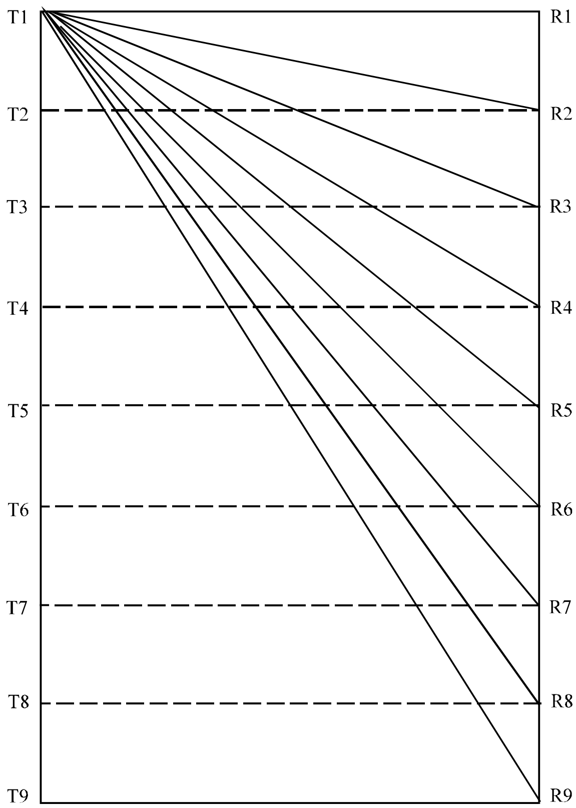

Fig. 2: Signal incentive and receiving mode.s

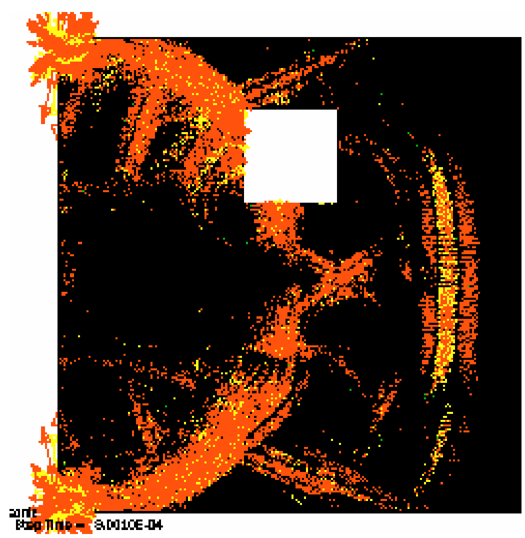

Fig. 3: Wave field of simulation process

Tomography results: According to forward calculation results, particle swarm optimization algorithm and improved particle swarm optimization algorithm were used to calculate the speed of sound value of each pixel unit;

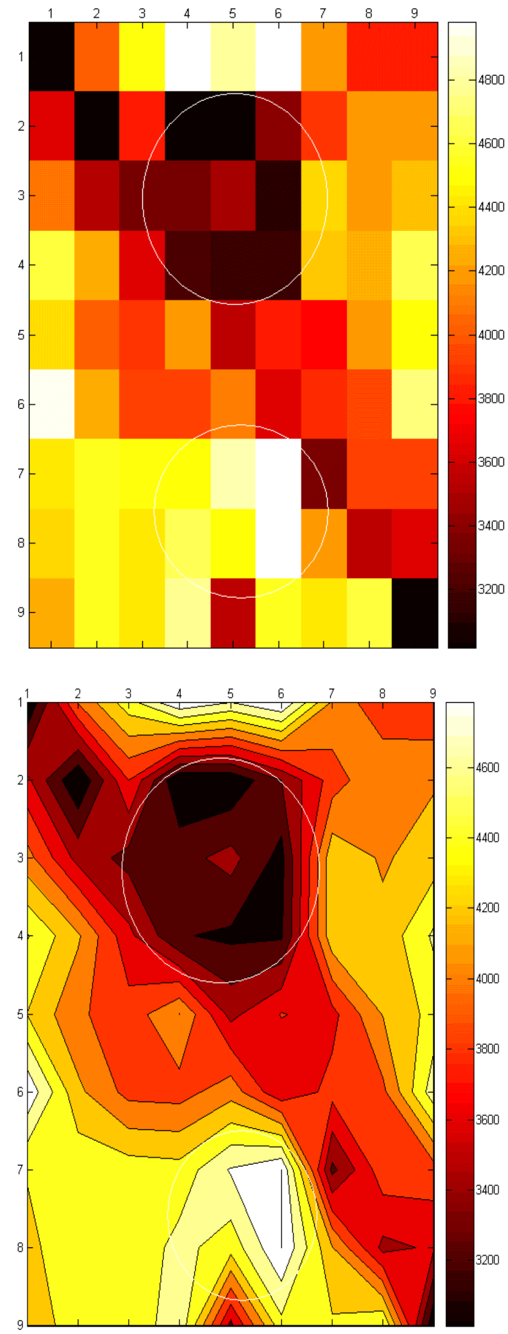

Fig. 4(a-b): Ultrasonic CT results by PSO

Finally to obtain sound velocity tomography result as shown in Fig. 4 and 5, respectively. Fig. 4a and 5a, respectively represent the pixel unit speed of sound imaging figure that obtained by the two algorithms, each pixel cell values corresponding to the velocity values of the corresponding positions of the concrete model. Fig. 4 b and 5b shows a contour plot of the speed and

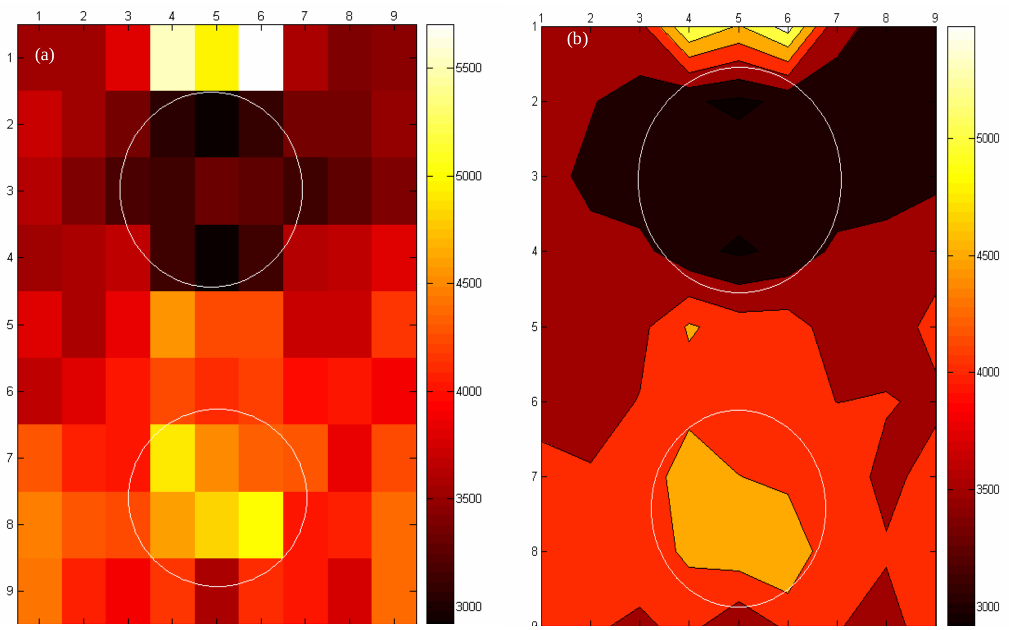

Fig. 5: Ultrasonic CT results by improved PSO

Table 2: Comparison of velocity values that calculated by the improved inversion

Algorithm	Speed of sound in concrete area (m sec^{-1})			Speed of sound in defect region (High-speed region/Low-speed region) (m sec^{-1})		
	True speed of sound	Speed of sound of inversion	Error (%)	True speed of sound	Speed of sound of inversion	Error (%)
Before improved	3892.7	4079.2	4.79	4175.3/3388.1	4089.9/3235.1	2.05/4.52
Improved		3851.5	1.06		4216.8/3295.7	0.99/2.72

the purpose of the contour map is to determine the defect region. The defective portion can be clearly distinguished from FIG, the part of the area marked out on contour map can be clearly distinguished as low-speed defect district, the area marked out at the bottom of the image can be clearly distinguished as the high-speed defect area. As can be seen that chromatography results of inversion algorithm improved smaller jumps and the image is more continuous, more obvious defect region by comparison. The results of the two inversion algorithm calculated data is in Table 2 and the speed by calculated is the average sound velocity. Comparing two inversion algorithm results can be seen that the improved algorithm is more accurate and realistic sound velocity value.

CONCLUSION

For particle swarm optimization algorithm is easy to fall into the local optimum and precocious problem, an improved particle swarm optimization algorithm is proposed. The particle swarm algorithm shortcomings can be overcome by introducing the simulated annealing algorithm with strong pop partial solution which can give full play to its intelligent global search capability and improve search accuracy. The improved algorithm is applied to the ultrasonic tomography of concrete structures and better imaging results are obtained. The numerical simulation results show that the imaging results obtained from improved algorithm is more stable, more accurate and calculate the average sound velocity closer to the true value under the same test conditions. The study has some reference value in structural safety assessment of practical engineering.

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REFERENCES

Chang, C.Y., Y.F. Lei, C.H. Tseng and S.R. Shih, 2010. Thyroid segmentation and volume estimation in ultrasound images. IEEE Trans. Biomed. Eng., 57: 1348-1357.

Chiu, C.C., C.H. Sun and W.L. Chang, 2011. Comparison of particle swarm optimization and asynchronous particle swarm optimization for inverse scattering of a two-dimensional perfectly conducting cylinder. Int. J. Applied Electromagn. Mech., 35: 249-261.

Das, A. and M. Bhattacharya, 2011. Affine-based registration of CT and MR modality images of human brain using multiresolution approaches: Comparative study on genetic algorithm and particle swarm optimization. Neural Comput. Appl., 20: 223-237.

Hosseini, Z., D. Levesque, M. Momayez and F. Hassani, 2008. Detection of inclined cracks inside concrete structures by ultrasonic SAFT. Proceedings of the 34th Annual Review of Progress in Quantitative: Nondestructive Evaluation, July 22-27, 2008, Golden, CO, USA., pp: 1298-1304.

Kennedy, J. and R. Eberhart, 1995. Particle swarm optimization. Proceedings of the IEEE International Conference on Neural Networks, November 27-December 1, 1995, Perth, Australia, pp: 1942-1948.

Li, Q., L. Shi, D. Liang and G. Li, 2008. Compensating method for transducers based on digital filtering in concrete test. J. Nanjing Univ. Aeronautics Astronautics, 40: 55-59.

Li, Q.F., H.G. Liu, H.C. Ma and Z.H. Chen, 2012. Study on improved computed tomography algorithm in concrete structure. Applied Mech. Mater., 189: 401-405.

Lin, W.Z., 2002. Viewing the evolution of nondestructive testing in civil engineering. Proceedings of the 5th World Conference on Non-Destructive Testing, Volume 24, October 21-24, 2002, Tokyo, Japan, pp: 123-125.

Sharma, N., A.K. Ray, S. Sharma, K.K. Shukla, L.M. Aggarwal and S. Pradhan, 2009. Segmentation of medical images using simulated annealing based fuzzy C means algorithm. Int. J. Biomed. Eng. Technol., 2: 260-278.

Shen, J.Z., Z.J. Li and Z.Y. Zhang, 2000. Nondestructive testing techniques and their applications in civil engineering. NDT, 22: 497-501.

Yamada, M. and H. Miyakoshi, 2008. Three-dimensional flaw shape reconstruction by linearized inverse scattering method. Doboku Gakkai Ronbunshuu A, 64: 133-141.

Zhu, H. and W. Ye, 2009. Application of particle swarm algorithm based on simulated annealing in variable cellular facility layout problems. Chinese J. Mech. Eng., 20: 181-185.

Zhu, J.L., L.D. Xiang and S.S. Liu, 2008. Ultrasonic sensor application in concrete nondestructive inspection system. Chinese J. Sensors Actuators, 21: 1290-1294.