A New Image Reconstruction Algorithm for Electrical Capacitance Tomography

Li Yan, Bao Peiquan, Cui Peng , Feng Li, Zhang Liyong

Harbin University of Science and Technology Harbin 150080, Province Heilongjiang, China, Phone:86-451-86390648 E-mail:liyan@hrbust.edu.cn

Abstract

In view of low precision of the reconstructed image of Electrical Capacitance Tomography (ECT) at present, a new image reconstruction method based on RBF neural network for Electrical Capacitance Tomography is proposed. Adaptive genetic algorithm is used to optimize the centers and widths of hidden layer of RBF network and Tikhonov regularization method is used to train the weights of RBF network. The simulation results for 12-electrode electrical capacitance tomography system illustrate that this method can improve the quality of reconstruction image obviously, testify the effectiveness of the proposed method.

Keywords: Electrical capacitance tomography; RBF; Adaptive genetic algorithm; Tikhonov regularization; Image reconstruction

1. Introduction

Electrical Capacitance Tomography (ECT) is an innovating technology for industrial two-phase visualization process. It has the advantages of simple structure, low cost, non-invasive, good safety and wide application in industry. It has become the main method of two-phase flow parameters detection. Image reconstruction algorithm [1,2,3] is one of the key technologies in ECT system. Now the conventional image reconstruction algorithms for ECT can not lead to reconstructed images with high resolution and accuracy due to few of projection data and are far away from the wide application in industry. Therefore, it is important and exigent to look for a better image reconstruction method for current fast developing two-phase detection in industry.

The unique non-linear mapping feature of RBF neural network [4,5] is fit for the non-linear soft field characteristics of ECT sensor. At the same time, genetic algorithm with high parallelity, randomness and adaptability, well suited to acquire optimal solutions of some complicated non-linear problems. In this paper, a novel method using RBF network with improved adaptive genetic algorithm and Tikhonov regularization method for ECT reconstruction algorithm is proposed and good image reconstruction results are obtained with this method, providing a new and effective approach for ECT image reconstruction.

2. System Structure and Model of Image Reconstruction for ECT

2.1. System structure of ECT

A typical ECT system consists of a capacitance sensor, a data acquisition system and the image reconstruction computer. The sensor is composed of 12

Proceedings of the 11th Joint Conference on Information Sciences (2008)
Published by Atlantis Press

measurement electrodes, 12 radial electrodes, shielding screen and insulating pipeline. The sensor transforms two-phase flow dielectric distributions into the sensor output capacitances, and the data acquisition system transforms these capacitances into digital and transmits them to the imaging computer, which completes the image reconstruction. The capacitance measurements is the projection data for image reconstruction The projection data provides the distribution information of two-phase media in the cross section field in pipeline. Based on the projection data, reconstruction images of cross-section field in pipeline can be reconstructed with feasible image reconstruction algorithm, extracting some characteristic information of two-phase such as phase concentration and phase volume fractions. N-electrode ECT sensor can get the number of capacitances are $C_N^2 = N(N-1)/2$ .The 12-electrode ECT system is shown in Fig.1.

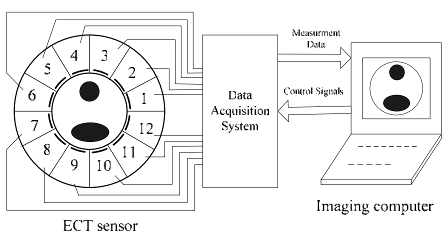


Fig. 1: ECT System

2.2. Image reconstruction model

In ECT, the capacitance value for any two electrode plates can be calculated on condition that ignoring the slightly influence of shielding layer outside the pipeline. The measuring capacitance between two electrode plates can be expressed by following integral equation.

$$C = \iint_D G(x,y) \cdot S(x,y,G(x,y))dxdy \quad (1)$$

After discretization and linearization, the equation above can be simplified to the following matrix equation:

$$\mathrm{C} = SG \qquad (2)$$

where the matrix dimension of C is $M \times 1$,it represents the normalized capacitance measurements, G is the distribution matrix of dielectric constant, $N \times 1$ in dimension, representing the gray value information of image reconstruction, S is sensitivity parameters matrix, $M \times N$ in dimension, reflecting the influence for dielectric constant distribution to capacitance.

Image reconstruction of ECT is a non-linear reverse and ill-posed problem. Its essence is to reconstruct the cross section images of the dielectric constant distribution by data projection (capacitance measurements) in pipeline. In this paper, imaging field is partitioned into 1200 pixel units with finite element method (FEM). Due to the number of pixels is much larger than that of projector data, so the formula (2) is a morbid equation, with infinite solutions, but has least-squares solutions. The model of inverse problem for image reconstruction can be expressed as follow:

$$G^+ = S^+ C \qquad (3)$$

where G^+ is the least-squares solution of the matrix G, representing the approximate gray value. S^+ is the generalized inverse matrix of S.

3. RBF Neural Network Learning Algorithm

3.1. Basic principles of RBF neural network

RBF (Radical Basis Function) network is a three-layer forward feedback neural network (Fig.2), consisting of an input layer, one or more hidden layers and an output layer. The input of input layer are normalized capacitance measurements Ci(i=1,2,…66).The middle is hidden layer of which neurons take the radial basis function as the activation functions. The output signals of output layer are grey values for image reconstruction, representing the distribution of dielectric constant in imaging field. In theory, RBF network can approach any non-linear mapping in infinite precision.

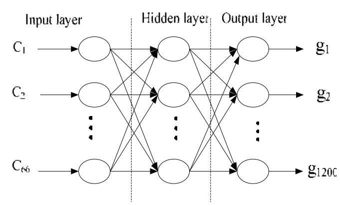


Fig.2: Structure of RBF network

$\Phi_i(x)$ is the activation function for the ith node of hidden layer:

$$\Phi_i = \exp\left(-\frac{\|x-u_i\|^2}{2\sigma_i^2}\right) \quad i=1,2,\ldots L \qquad (4)$$

where $x \in R^m$ is input vector, μ_i is the center of Gaussian distribution curve of the ith hidden layer neuron, σ_i is the width (radius) of hidden layer neurons of i-node, and L is the number of neurons in hidden layer. RBF network model is shown as follow:

$$Y(x, \Psi_{(\mu_i, w_i, \sigma_i)}) = \sum_{i=1}^{L} w_i \Phi_i(x) \qquad (5)$$

It is transformed into matrix equation:

$$Y = \Phi W \qquad (6)$$

where Y is output vector, $1 \times S$ in dimension, W is weight matrix, $L \times S$ in dimension, Φ is output vector of hidden layer, $1 \times L$ in dimension.

3.2. Improved RBF Network Algorithm Based on Genetic Algorithm

3.2.1 Genetic coding

In view of large population size and coding length in experiment, float encoding is superior to binary code. The centers and widths of the hidden layer nodes are encoded with float encoding (Fig.3).In Fig.3, L is the number of bytes taken up for one center in coding and N is the number of neural nodes in hidden layer. Thus an chromosome represents the whole RBF network. Calculation accuracy and searching efficiency can be improved significantly.

a_{11}	a_{12}	…	a_{1L}	…	a_{N1}	a_{N2}	…	a_{NL}	c_1	c_2	…	c_N

Fig.3: Coding format of chromosome

3.2.2 Fitness function construction

The fitness function is used to determine the genetic probability to be selected to the next generation for one individual, leading to selection and optimal solution searching of genetic algorithm. It is set as the reciprocal of the accumulative total, which is the absolute value of the difference between expectation and the actual output. It reflects virtues or defect degree of each individual clearly. The fitness function of individual i is expressed as follow:

$$f(i) = 1/E(i) = 1/\sum_{k=1}^{N}\sum_{j=1}^{S} | d_{kj} - y_{kj} | \qquad (7)$$

3.2.3 Selection crossover and variation

In genetic algorithm, the roulette wheel selection with excellent individual retention is adopted. First, chose a few best fitness individuals to the next generation directly. Then chose other individual until the population size is as large as that of the last generation.

The aim of crossover is to create next generations, providing new individuals for genetic searching. While variation is an assistant strategy in creating new individual, promotes the local searching ability of genetic algorithm. Crossover probability and variation probability are the key factors to the efficiency of genetic algorithm. However, it is very hard to get best values, the mode of genetic solution may be damaged or very slow in genetic searching in the case of large or small crossover probability and variation probability. All these are not good for evolution solving. Srinvivas et al proposed an genetic adaptive algorithm [6]. In this algorithm, crossover probability and variation probability can change according to individuals' fitness function value. When the fitness function value of an individual is smaller than the average fitness function values, this individual is bad and the crossover probability and variation probability will become larger. Or else, the two probabilities will get smaller. To a great extent, this strategy solved the problem mentioned above. However, the crossover probability and variation probability will tend to zero when one individual's fitness function value is very close or equal to the group's largest fitness value. This is very harmful to early evolution for increasing the possibility of getting local optimal solution. In order to solve this problem, an improved genetic algorithm is presented in this paper. On the assumption that two parent individuals are X_1^t and X_2^t, the child individuals are shown as follows:

$$\left.\begin{aligned} X_1^{t+1} &= X_2^t + p_c\,(X_1^t - X_2^t) \\ X_2^{t+1} &= X_1^t + p_c\,(X_2^t - X_1^t) \end{aligned}\right\} \tag{8}$$

$$p_c = \begin{cases} P_{c1} - \dfrac{(p_{c1}-p_{c2})(f-f_{\max})}{f_{\max}-f_{avg}}, & f \geq f_{avg} \\ P_{c1}, & f < f_{avg} \end{cases} \tag{9}$$

Where f_{max} is the largest fitness function value of number t generation, f_{avg} is the average fitness function value, while f is the larger fitness function value between two parents, P_C is adaptive crossover probability, $P_{c1}=0.9$, $P_{c2}=0.6$.

In order to realize the variation, gene values encoded are displaced in adaptive variation probability. Adaptive variation operator is expressed as follows:

$$x' = p_m\left(U_{\max} - U_{\min}\right) + U_{\min} \tag{10}$$

$$p_m = \begin{cases} P_{m1} - \dfrac{(p_{m1}-p_{m2})(f_{\max}-f')}{f_{\max}-f_{avg}}, & f' \geq f_{avg} \\ P_{m1}, & f' < f_{avg} \end{cases} \tag{11}$$

where x' is the value of the new gene after variation, $[U_{max}, U_{min}]$ is the value range of individual x before variation, f′ is the fitness function value of individuals before variation. P_m is the adaptive variation probability, $P_{m1}=0.1$, $P_{m2}=0.001$. By improving, the crossover probabilities and variation probabilities of the individuals with the largest fitness function values are amplified to P_{c1} and P_{c2} respectively, not zero, avoiding the approximate stagnation state of evolution solving. In addition, child individuals can replace parent individuals on condition that the fitness function values of child individuals are larger than that of the parent individuals. After the improvement in crossover and variation, the diversity of the population is maintain by the new genetic algorithm, avoiding premature convergence, and promotes the quality and efficiency of evolution solving. All these are available for obtaining optimal solution.

3.2.4 Calculation of weights

Image reconstruction of ECT is an inverse problem with ill-posed solutions. Tikhonov regularization method is an improved generalized inverse algorithm based on stable least-squares method. Utilizing Tikhonov regularization method [2] to solve this problem namely chose a constraint to keep the solution stable. In RBF network with N learning samples and S output nodes, error objective function is set as follow.

$$E = \frac{1}{2}\sum_{k=1}^{N}\sum_{j=1}^{S}(d_{kj} - y_{kj})^2 + \lambda\|PY\|^2 \qquad (12)$$

where ykj is the output of output layer, while dkj is the actual output of output layer, P is linear differential operator reducing the concussion of function, λ is a regularization parameter, λ = 0.001. After the calculation of centers and widths of hidden layer neurons, weights W can be calculated by equation (6). Due to output vector of hidden layer is irreversible, so weights W can be worked out according to Tikhonov regularization method. W is shown as follow:

$$W = (\Phi^T\Phi + \lambda I)^{-1}\Phi^T Y \qquad (13)$$

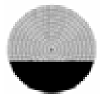
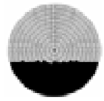
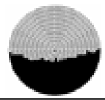
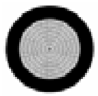
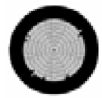
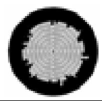
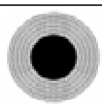
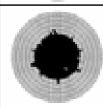
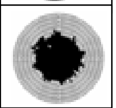
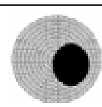
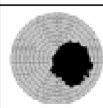
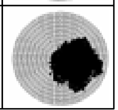
where Φ^T is the transpose matrix of matrix Φ, and I is the identity matrix.

4. Simulation Results of Image Reconstruction

In the simulation experiment towards 12-electrode ECT system, there are 401 samples. The training sample set is obtained by simulation. The input of the RBF neural network are 66 normalized capacitance measurements and the output are 1200 pixels´ gray values in the imaging field in pipeline. In experiment, two mediums with dielectric constants are 1 and 6 is defined, the output threshold is set 3.5, if the output is larger than 3.5, it will be judged as high dielectric constant medium. Or else, it is the low one. Imaging experiment was implemented towards typical flows of two-phase including stratified flow, annular flow, core flow and eccentricity flow. The experimental result is shown in Table.1.For comparison, the classic LBP (Linear Back Projection) algorithm for ECT was also implemented in this experiment. The reconstructed images of high dielectric constant medium are shown in black, and the white region represents low dielectric constant medium.

Obviously the images reconstructed with improved RBF neural network method are of high resolution and good precision. Accuracy, which is defined as the percentage of correct pixels reconstructed in one image. The typical flows Accuracies reached 98.67%, 99.08%, 98.50% and 96.41% respectively, while the Accuracies of reconstructed images obtained by LBP method reached 85.41%, 90.26%, 87.73% and 82.73%. Apparently the quality of reconstructed images obtained by improved RBF neural network method is better than that of reconstructed images with conventional LBF algorithm.

Table1 Experimental results of image reconstruction

Eccentric Flow	Original Flow	RBF	LBF
Stratified Flow			
Annular Flow			
Core Flow			
Eccentric Flow			

5. Conclusion

A non-linear mapping model between RBF neural network and the image to be reconstructed can be established. Images with high precision for ECT system can be obtain reconstructed by the improved RBF neural network method combined with adaptive genetic algorithm and Tikhonov regularization method. The average Accuracy reached 98.18% prior to LBP method, improving the precision of conventional reconstruction images greatly. In addition, the experiment result of eccentric flow show that the generalization ability of RBF network presented can be improved by increasing irregular flow patterns in training.

6. Acknowledgments

This work is supported by natural science foundation of China (60572153), natural science foundation of Heilongjiang province (F200505), science and technology development project of Heilongjiang provincial science and technology (GC05A510), science and technology development project of Heilongjiang provincial education bureau (11511078, 1054G014, 10551043), science and technology development project of PRC education ministry (204043).

7. References

[1] Haiqing Li, Zhirao Huang, “Special Detection Technology and its Application”, Zhejiang University Press, pp.19-35, 2000.

[2] Peng Lihui, Lu Geng, Yang Wuqiang, “Image reconstruction algorithm for electrical capacitance tomography: state of the art”, Journal of Tsinghua University (Science and Technology), 44 (4):478-484, 2004.

[3] Wang Weiwei, Wang Baoliang, Huang Zhiyao, LI Hai-qing, “Voidage measurement based on genetic algorithm and electrical capacitance tomography”, Journal of Zhejiang University, 6A(12):1441-1445, 2005.

[4] Wei Ying, Zhao Jinchuang, Wang Shi, and Lu Zengxi, “Research of the Image Reconstruction Algorithm for Electrical Resistance Tomography”, Chinese Journal of Scientific Instrument, 22 (4) :369-371, 2001.

[5] Srinivas M, Patnaik L M, “Adaptive probabilities of crossover and mutation in genetic algorithms”, IEEE Trans. on Syst. Man and Cybern., 24(4):656-667, 1994.

[6] Nooralahiyan A. Y., Hoyle BS, “Three-component tomographic flow imaging using artificial network reconstruction”, Chemical Engineering Science,52 (13) :2139-2148, 1997.