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An Image Reconstruction Method Based on Simulated Annealing and Back Propagation Algorithm for Electrical Capacitance Tomography

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Abstract: For solving low convergence rate and being vulnerable to fall into a local minimum in BP neural network during training process, a new ECT image reconstruction algorithm based on neural network and Simulated Annealing Algorithm (SAA) is brought forward. In this method, an additive momentum is considered for weight adjustment in BP neural network and adaptive mechanism is adopted to adjust study rate for better performance in convergence of neural network. In addition, the training neural network is guided by SAA to ignore local minimum and is optimized for global minimum. Simulation results show that according to the algorithm based on neural network and SAA, high quality reconstruction images are obtained, which provides a new method for the study of ECT system.

Key words: Electrical capacitance tomography, image reconstruction, BP neural network, simulated annealing algorithm

INTRODUCTION

ECT (Electrical Capacitance Tomography) is a new Process Tomography (PT) technology, which is mainly applied in detecting multiphase-flow in industrial pipelines. Compared to the other technologies, there are some advantages such as simple structure, low cost, non-intrusion and good performance of ECT system and it is widely used in industrial applications. In ECT, image reconstruction is one of the key technologies. At present, Linear Back Propagation (LBP) and some iteration algorithms are applied in reconstructing. In LBP method, reconstruction is finished quickly, but with poor quality, from which there are only several qualitative parameters (Deyun *et al*., 2009). In some iteration reconstruction algorithms, high quality images are obtained, but with low speed because of more iterations steps, which cannot meet the real-time requirement in industry (Li *et al*., 2011). Recently, Artificial Neural Network (ANN) is a hot research in ECT system and there are more studies on image reconstruction algorithms based on ANN, especially back propagation neural network. Applying BP algorithm on image reconstruction, the precise is improved, but the speed of convergence is slow down because of complex training study and it is easy to fall into local minimum.

In this study, for solving the flaws of BP neural network algorithm, the simulated annealing algorithm is adopted (Simulated Annealing-Back Propagation Algorithm, SA-BP) to optimize the speed and precise of reconstructing image to satisfy the real-time requirement in industrial production process.

BASIC PRINCIPLE OF ECT SYSTEM

ECT system is composed of capacitance transducers, data acquisition system and imaging computer, which are shown in Fig. 1. When distribution of medium in pipeline changes, the capacitance values between a pair of plates are changed. Based on this principle, the distribution of two-phase flow in pipeline can be inversed according to the capacitance measurement values.

In an N-electrode ECT system, the number of independent capacitance values M can be computed as followed process: These electrodes are sequentially numbered as 1, 2, …, N. During the whole measurement process, the capacitance values between electrode pairs of 1-2, 1-3, … , 1-12, 2-3, 2-4, … , 2-12, … , 11-12 are measured (in every measurement, the number before hyphen electrode is as active electrode). So in an N-electrode ECT system, the number M can be computed as the formula:

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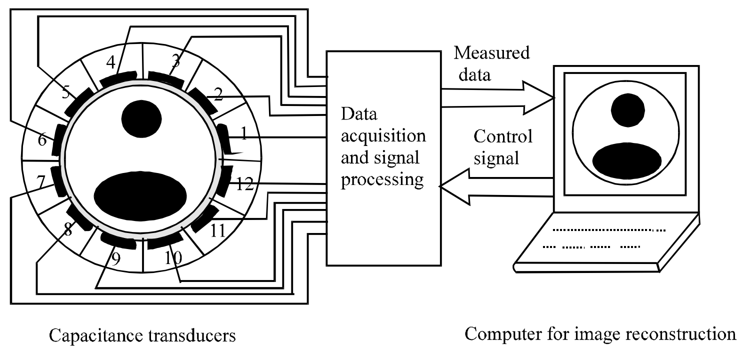


Fig. 1: Structure of 12-electrode ECT system

$$M = C_N^2 = \frac{N.(N-1)}{2}$$

In this study, 12-electrode ECT system is studied and M can be computed as 66.

Currently, most ECT image reconstruction algorithms are based on the linear model mapping permittivity distribution to capacitance values. After discretization, linearization and normalization, the model can be showed as followed:

$$C = SG \tag{1}$$

In (1), $C \in R^m$ is normalized capacitance values vector, $S \in R^{m \times n}$ is coefficient matrix (sensitivity matrix) and $G \in R^n$ is normalized image pixel vector of medium distribution in pipeline. The target of ECT image reconstruction is to obtain permittivity distribution G according to the capacitance values C.

ANALYSIS OF IMAGE RECONSTRUCTION APPLYING BP NEURAL NETWORK

BP neural network: In many artificial neural network models, BP network is a typical multi-layer feed forward neural network and error back-propagation algorithm is usually used in training. The objective function of BP neural network is the network sum of errors squares and according to gradient approaches, the minimum value of the function can be obtained.

There are 3 layers in neural network: input layer, hidden layers and output layer. Neurons in each layer are transmitted to the output of the next layer. There are 2 phases in training process (Yang and Peng, 2003). The forward propagation of input signal and the back propagation of error transmission. In forward propagation, the signal is transmitted from input layer to hidden layers and then is transmitted to output layer. The input value of every layer is only decided by the former layer. If the output of network is inconsistent with the expected sample, the errors are transmitted to the former layer and by adjusting weights between layers, the errors will be minimized (Tan *et al*., 2011).

Figure 2 shows a 3-layer forward neural network with a hidden layer. In hidden layer and output layer, sigmoid function is selected as the activation function. There are N input nodes, K hidden layer nodes and M output nodes. When P samples are input to the neural network, the pth input vector is denoted as $X_p = (x_{p1}, x_{p2}, x_{pN})^T$, expected output vector is denoted as $t_p = (t_{p1}, t_{p2}, t_{pN})^T$, the mth output node is denoted as O_{pm}, the kth output of hidden layer node is denoted as Y_{pk}, the weight between the kth hidden layer node and the mth output node is denoted as ω_{nk} and the weight between the nth input node and the kth hidden layer node is denoted as ϖ_{nk}.

In input layer:

$$O_{pm}(i) = f\left(\sum_{k=1}^{N} \omega_{km}(i) y_{pk}(i)\right) \tag{2}$$

In hidden layer:

$$y_{pk}(i) = f\left(\sum_{n=1}^{N} \varpi_{nk}(i) x_{pn}\right) \tag{3}$$

In Eq. 2 and 3, the transfer function f (x) is single polarity sigmoid function, which is shown in (4):

$$f(x) = \frac{1}{1+e^{-x}} \tag{4}$$

Principle of ECT image reconstruction based on BP neural network: In ECT image reconstruction algorithm based on BP neural network, the key thinking is to build a model mapping the capacitance values C to image pixel

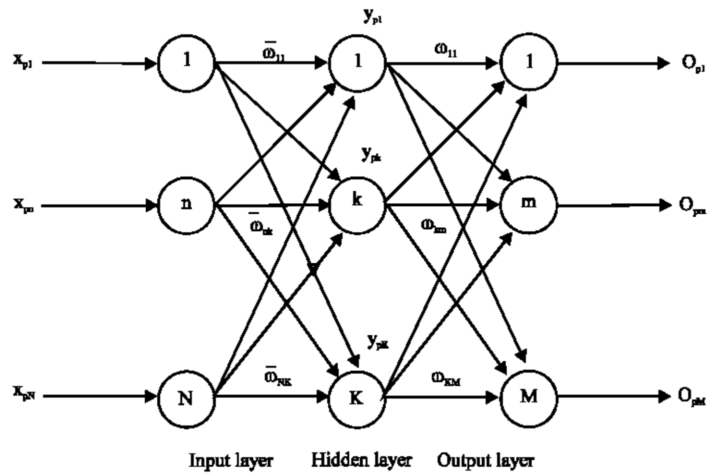


Fig. 2: Structure of BP neural network

gray value G and then train the network according some samples (Deyun *et al*., 2005). In this study, a 3-layer BP neural network is constructed to approximate the mapping of f: C→G. The 3-layer BP network includes input layer, hidden layer and output layer (Zuo-Ping *et al*., 2008). The input and output vectors of ECT system are special vectors with many dimensions. The signal in first layer of neural network is the measurement capacitance values C_i (i = 1,2,...,66). The second layer is hidden layer and the third layer is output layer. The output signal is image pixel gray value g_i (i = 1,2,...,1296) (in this paper, there are 1296 output nodes in BP neural network).

The quality of reconstruction image in BP neural network based on gradient descend is well improved compared to the other methods, but there are disadvantages such as low convergence rate and being vulnerable to fall into a local minimum. So, in this study, it is optimized in two aspects: Firstly, momentum and adaptive adjustment learning rate are introduced in basic BP neural network, which improve the convergence rate of network; secondly, based on the designed network, simulated annealing algorithm is adopted to guide the network out of local minima to global convergence.

SIMULATED ANNEALING-BACK PROPAGATION ALGORITHM

Optimization by momentum and adaptive learning rate: To improve the convergence rate of BP neural network, momentum and adaptive learning rate are considered to optimize the algorithm. The weights are adjusted as followed:

$$\Delta\omega_{ji}(t) = \eta\delta_{kj}(t)o_{ki} + \alpha\Delta\omega_{ji}(t-1)\alpha \in (0,1) \tag{5}$$

In Eq. 5, α is the momentum coefficient. Eq. 5 shows that one part of weight in (t-1)th is added in the tth weight adjustment, which can stabilize the network and improve the training speed.

In the training process of BP network, the selection of the step η is important. A larger η can accelerate convergence rate, but makes network unstable, while a smaller η can avoid an unstabilized network, but the convergence rate is slow (Marashdeh *et al*., 2006; Liu and Jie, 2008). For consideration of these factors, a better method is to adjust learning rate adaptively. Eq. 5 can be considered as the first-order difference equation of $\Delta\omega_{ji}$ and to solve the equation, Eq. 6 can be deduced:

$$\Delta\omega_{ji}(n) = \eta\sum_{t=0}^{n}\alpha^{n-1}\delta_{kj}o_{kj} = -\eta\sum_{t=0}^{n}\alpha^{n-1}\frac{\partial E(t)}{\partial\omega_{ji}(t)} \tag{6}$$

When $\partial\omega_{ji}$ is positive as same as in the previous iteration (or they are all negative), when the sum multiplied with weights is large, $\Delta\omega_{ji}$ (n) is also large, which increase the adjustment rate of ω. When $\partial\omega_{ji}$ (t) is positive/negative and in the previous iteration is negative/positive, it is unstable in network. In this situation, $\Delta\omega_{ji}$ (n) is small because of the effect of the weights, which brings stability in network.

BP neural network optimized simulated annealing algorithm: BP image reconstruction algorithm based on gradient descent is a new and an effective intelligent optimization method, but because of local minimum in optimized surface, it is easy to fall into local minimum and difficult to reach the global minimum (Sheng *et al*., 2002). Simulated Annealing Algorithm (SAA) is a kind of stochastic heuristic search method (Wasan, 2008; Tabriz *et al*., 2009). In search strategy of SAA, random factors are introduced and in some probability the bad function value is accepted and the probability decreased along with the bad values (Kamyab *et al*., 2008). The search strategy is optimal in avoiding to falling into the local minimum (Samsudin *et al*., 2010), so which is adopted to train the neural network to find the global minimum (Zhao *et al*., 2010).

In BP neural network optimized by simulated annealing algorithm (SA-BP), the main idea is to add the momentum and adaptive learning rate to train BP neural network. In the process of training, when falling into the local minimum, SAA is invoked to jump the situation and the neural network is trained sequently until find the global minimum. The process of SA-BP is shown as followed:

- Initialize the weight matrix W, MinError is denoted as the minimum error in neural network
- Define momentum and adaptive learning rate to optimize BP neural network, train the network and compute the value of E (m)
- If the precision of error satisfies the convergence requirement: E (m) MinError and go to step (9)
- If sequent n differences of errors: $\Delta E = E(m) - E(m-1)$ are less than a minimum value λ, it means the neural network has fell into the local minimum. Record the error: $E_0 = E(m)$ and invoke SAA, go to step (6). (In this study, n = 10, $\lambda = 10\times10\text{-}10$)
- Update weight matrix W, m = m+1. Go to step (2) to start the next round of BP neural network training
- Invoke SAA, E (m) = SA (W)
- If the precision of error satisfies the convergence requirement: $E(m)<E_0$, go to step (9), finish the algorithm
- If the neural network has jumped local minimum, which means there is E (m)<MinError, go to step (2) to start the next round of network training; otherwise go to step (6) to train the network under the control of SAA until out of local minimum
- The training of network is finished

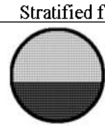
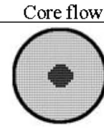
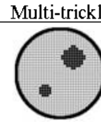
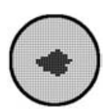
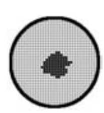
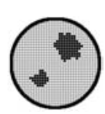
SIMULATION AND EXPERIMENT

In this study, oil-water two-phase flow is studied in 12-electrode ECT system. There are 1296 pixel units in pipeline section divided by 36×36 according to finite element method and 982 units in effective imaging section. In 3-layer BP neural network, a mapping approximate relation f: C→G is adopted in hidden layer and the threshold values can be adjusted with weight values in neurons of hidden layer and output layer. In hidden layer, sigmoid function is selected as activation function. The source data comes from finite element method of two-phase flow regimes, which is input to train the neural network and the output is the image pixel matrix of reconstruction.

According to SA-BP algorithm, BP neural network is designed and trained for 4 typical flows: Stratified flow, core flow, multi-trickle flow and annular flow. In experiment, the results in LBP image reconstruction algorithm and Landweber iterative image reconstruction algorithm are obtained to compare to this method, which is shown in Table 1. The black area is water and the white area is the oil.

The results show that for typical flow regimes, the precise and quality in SA-BP method for reconstructing the image are better than the image in LBP and Landweber and the error is small in SA-BP, which supplies a new method to image reconstruction in ECT system.

Table 1: Comparison of reconstructed images

Parameters	Stratified flow	Core flow	Multi-trickle flow	Annular flow
Original				
LBP				
BP				
SA-BP				

LBP = Linear back propagation, BP = Back propagation, SA-BP = Simulated annealing-back propagation

CONCLUSION

As a process Tomography technology based on capacitance sensitivity principle, ECT is widely used in industry. In ECT system, the number of capacitance values is smaller than the number of pixels in reconstructed image, which is called ill-posed problem. There are advantages such as excellent nonlinear mapping and associative memory in neural network, which can solve the ill-posed problem in ECT system. In this study, to solve low convergence rate and being easy to fall into the local minimum, simulated annealing-back propagation Algorithm (SA-BP) is brought forward to optimize the image reconstruction, which assures a stable network and improve the convergence rate. The simulation results show that the accuracy of reconstructed image is improved and proves SA-BP is an effective image reconstruction algorithm.

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