Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 14 (2): 137-143, 2014
ISSN 1812-5654 / DOI: 10.3923/jas.2014.137.143

A Novel Image Reconstruction Algorithm Based on Pulse Coupled Neural Network for Electrical Capacitance Tomography System

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Abstract: A novel image reconstruction algorithm which is based on Pulse Coupled Neural Network (PCNN) is presented in this study. This algorithm is used to solve "soft-field effect" and ill-posed problems in Electrical Capacitance Tomography Technology (ECT). Based on the analysis of the basic principle of electrical capacitance tomography and PCNN, the calculation of PCNN and the calculation steps of automatically setting the parameters are deduced for solving ECT inverse problem. Experiment and simulation results indicate that the algorithm can provide high quality images. It has the advantages of favorable stabilization and high speed of reconstructing image. It is easier to implement compared with Linear Back Projection Algorithms (LBP), Landweber algorithms and conjugate gradient algorithms (CG). This new algorithm presents a feasible and effective way to research the image reconstruction for electrical capacitance tomography system.

Key words: Electrical capacitance tomography, image reconstruction, adaptive rules, pulse coupled neural network

INTRODUCTION

Flow tomography technology is a new technology which has developed rapidly in recent years and the technology in solving the problem of multiphase flow detection has great developmental potential and wide industrial application prospect. Electrical capacitance tomography technique has the advantages of low cost, wide application range, simple structure, non-invasive, good safety performance and so on (Loser *et al*., 2001). The electrical capacitance tomography system has inherent characteristic of nonlinear. The number of capacitance values (projection data) which is independently measured is limited and it is far less than the number of pixels of reconstructed image. There is no analytical solution of inverse problems. At the same time, the stability of solution for the ECT system is poor because of the nonlinear and "soft field effect" and its ill-posedness is very serious, therefore, image reconstruction is difficult (Liu *et al*., 2009).

Whether the algorithm can reconstruct images which are very close to the original images or its speed of reconstructing images (Ghanbari, 2008) is fast, it decides the quality of the ECT images. LBP, Landweber iterative algorithm, projection Landweber iterative algorithm (Gosselin *et al*., 2009) and CG are common algorithms which are used for ECT image reconstruction.

LBP is simple and it can fast reconstruct image. But the quality of image is relatively poor and it is only a qualitative method (Zhiyao *et al*., 2009). The projection Landweber iterative algorithm can obviously improve the stability of iteration (Daoye *et al*., 2009) and it can also effectively control the noise. But when it processes the complicated flow pattern, it usually requires a large number of iterations in order to achieve satisfactory results. So this defect restricts its applications (Zhiyao *et al*., 2009). CG is suitable for the coefficient matrix which is symmetric and positive definite. The image reconstruction time of this method is short and it also has fast convergence for simple flow. But the effect of the image is not ideal for the complicated flow pattern. In order to solve above mentioned problems, this study proposes image reconstruction algorithm which is based on adaptive Pulse Coupled Neural Network (PCNN).

MATERIALS AND METHODS

Basic principle of electrical capacitance tomography system: The working principle of electrical capacitance tomography is as follows: The capacitive sensor array is

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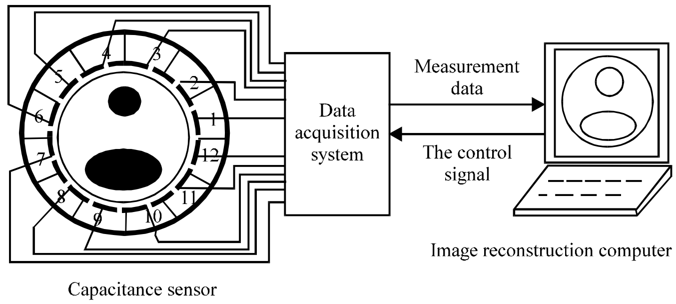

Fig. 1: Composition of electrical capacitance tomography system with 12 electrodes

installed around the measured filed. When the density or distribution of the dielectric changes, the sensors will detect the changes of capacitance values. Then it will transmit these values to the computer to process and the computer can reconstruct the distribution of the dielectric section. Finally the computer will calculate the parameters of multiphase flow. ECT system is mainly composed of capacitor sensors, data acquisition system and the computer which is responsible for reconstructing images (Yang, 2010). The physical structure is shown in Fig. 1.

At present, most of the ECT image reconstruction algorithms are based on the linear model (Li and Yang, 2009). In the model, the dielectric constant is mapped to the capacitor. After discretization, linearization and normalization (Grudzien *et al*., 2010), the model can be expressed as:

$$C = S\epsilon \tag{1}$$

In the equation, $C\in R^m$ represents the capacitance measurement value, $C\in R^{mHn}$ represents the coefficient matrix (sensitivity matrix), $\epsilon\in R^n$ represents the medium distribution image vector. The task of ECT image reconstruction is to solve the distribution of dielectric constant ϵ with the given capacitance value C. The inverse problem of ECT system is to reconstruct medium dielectric constant distribution map in the detection zone by observing and measuring the capacitance measurement values (Ge and Song, 2010). That is to solve the gray values of each pixel in the imaging area.

Image reconstruction algorithm based on adaptive pulse coupled neural network: Pulse coupled neural network is also known as the third generation artificial neural network. It is a feedback network which is composed of a number of interconnecting neurons. This structure is inspired by biological visual cortex model (Cheng *et al*., 2008). Generally, each neuron of PCNN is composed of

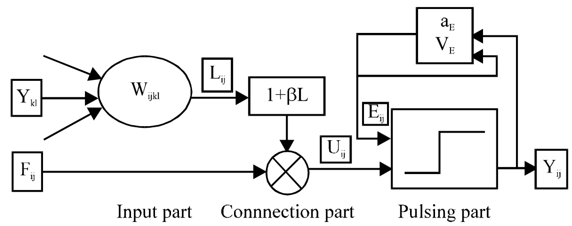

Fig. 2: Single neuron model of simplified pulse coupled neural network

three parts: Input section, connecting part (modulation section) and pulse generating part. Single neuron model is shown in Fig. 2.

Image reconstruction algorithm: The capacitance values are measured between electrodes and they are used as original data of image reconstruction in ECT system. But these values are very different. They can vary several times to hundreds of times. So it is easy to make a big error in the result and this goes against the improvement of calculation accuracy. In the prior to image reconstruction, the measured capacitance and dielectric constant are normalized. The normalized form of capacitance C and dielectric constant variation ϵ are:

$$\lambda = \frac{C_H}{C} \bullet \frac{C - C_L}{C_H - C_L},\ k = \frac{\varepsilon_H}{\varepsilon} \bullet \frac{\varepsilon - \varepsilon_L}{\varepsilon_H - \varepsilon_L} \tag{2}$$

In the equation: C_L and C_H, respectively represent the capacitance between electrodes when measuring area is filled with air and the capacitance of electrodes when measuring area is filled with solid medium. ϵ_L and ϵ_H respectively represent air and solid medium dielectric constant. represents gas/solid two-phase hybrid dielectric constant in the measuring zone.

After normalized, Eq. 1 of ECT system (the sensitivity of each pixel in the sensor measuring the area is not equal) can be transformed into:

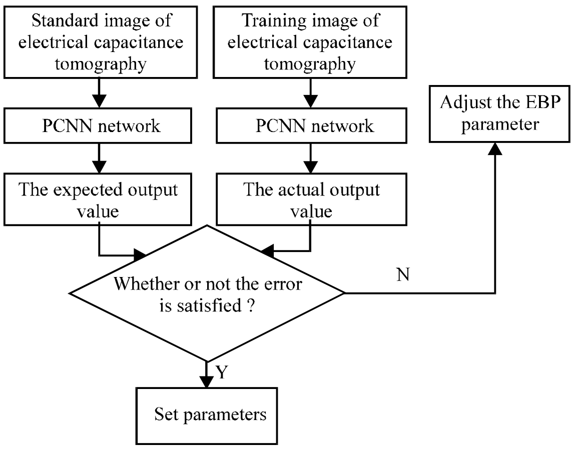

Fig. 3: Structure diagram of training system of adaptive pulse coupled neural network

$$\lambda = SK \tag{3}$$

In the equation: λ represents normalized capacitance matrix, K represents normalized effective dielectric constant, S represents sensitivity coefficient matrix. Therefore, the inverse problem can be expressed as $K^+ = S^+\lambda$, in the equation, K^+ is the least square solution of K, that is estimated gray value of reconstructing image, S^+ is the generalized inverse matrix of S. The Eq. 3 is applied to the discrete mathematics equations of PCNN (Cheng, 2009) and the following equation can be obtained:

$$\lambda_{ij}[n] = \exp(-a_F)\lambda_{ij}[n-1] + V_F \sum M_{ijkl} K_{kl}[n-1] + P_{ij} \tag{4}$$

$$L_{ij}[n] = \exp(-a_L)L_{ij}[n-1] + V_L \sum M_{ijkl} k_{kl}[n-1] \tag{5}$$

$$U_{ij}[n] = \lambda_{ij}[n](1 + \beta L_{ij}[n]) \tag{6}$$

$$E_{ij}[n] = \exp(-a_E)E_{ij}[n-1] + V_E \sum \lambda_{ij}[n]) \tag{7}$$

And:

$$\begin{cases} K_{ij}[n] = 1,\ U_{ij}[n] \rangle E_{ij}[n] \\ K_{ij}[n] = 0,\ \text{otherwise} \end{cases} \tag{8}$$

The subscript ij represents neuronal labeling. λ_{ij}, L_{ij}, U_{ij} and E_{ij}, respectively represent feedback input, connecting input, internal activities and dynamic threshold of the N_{ij} capacitance value in the matrix (Ma and Qi, 2006). M and W represent connection weight matrixes (generally W = M). V_F, V_L and V_E, respectively represent amplification factors. a_F, a_L and a_E, respectively represent time decaying constant and n represents the iteration number. K_{ij} represents output with two values, that is the image pixel gray value.

Principle of automatically setting parameters in adaptive pulse coupled neural network: In order to get optimal output, the algorithm uses BP algorithm ideas. It also uses the EBP criterion (LMS criterion and the gradient descent method) as PCNN learning standards. The adaptive parameter adjustment is proceed with the ignition cycle so as to achieve an adaptive pulse coupled neural network. The structure of the system is shown as (Fig. 3).

Ignition cycle analyzes the ignition statistical characteristics of each pixel and it can specifically and explicitly quantize the physical relationship between input and output of PCNN model:

$$T(N_{ij}) = \frac{1}{\alpha_E} \mathrm{In}(\frac{V_E}{U_{ij}}) \tag{9}$$

The Eq. 6 is substituted into Eq. 9, then the following equation can be obtained:

$$T(N_{ij}) = \frac{1}{\alpha_E} \mathrm{In}(\frac{V_E}{\lambda_{ij}[n](1+\beta L_{ij}[n])}) \tag{10}$$

There are four main parameters: W, β, α_E and V_E. The setting of connecting matrix is relatively simple and its value is the inverse of square of the distance between pixels. The setting values of the other three major parameters can be obtained by using adaptive algorithm according to the desired output. It is assumed that each neuron in PCNN is restarted only once before ignition.

If focusing on neurons of PCNN, the criterion of mean square error is as follows:

$$MSE = \frac{1}{2}(T_{desire} - T_{actual})^2 \tag{11}$$

The corresponding partial differential item is as follows:

$$\frac{\partial MSE}{\partial V_i}(V_i^{old}) = -(T_{desire} - T_{actual})\frac{\partial T_{actual}}{\partial V_i} V_i^{old} \tag{12}$$

Replacing the second T_{actual} in Eq. 12 with T, then adaptive rules of each variable can be obtained as follows:

$$V_i^{new} = V_i^{old} + \eta(T_{desire} - T_{actual})\frac{\partial T_i}{\partial V_i} V_i^{old} \tag{13}$$

There are three key parameters (connecting strength β, time attenuation constant of dynamic threshold a_E and dynamic threshold amplitude constant V_E) in PCNN. Equations which are used to automatically set these parameters can be deduced according to the above-mentioned rules.

Connecting strength β is one of important parameters of all parameters in PCNN, it directly influences the roughness of texture of the result image when it processes the image by using PCNN. In order to get the adaptive adjustment rule of connecting strength β, firstly partial differential equations of connecting strength β which is corresponding to firing cycle T should be solved:

$$\frac{\partial T}{\partial \beta}=\frac{1}{\partial_E}\frac{\lambda(1+\beta^*L)}{V_E}\frac{\partial(\frac{\lambda(1+\beta^*L)}{V_E})}{\partial\beta}=\frac{L}{\alpha_E(1+\beta^*L)} \quad (14)$$

Adaptive rule of parameter β can be obtained according to Eq. 13:

$$\begin{aligned}\beta^{new}&=\beta^{old}-\eta^{\beta}(T_{desire}-T_{actual})\frac{\partial T}{\partial\beta}\\&=\beta^{old}-\eta^{\beta}(T_{desire}-T_{actual})\frac{-L}{\alpha_E(1+\beta^*L)}\end{aligned} \quad (15)$$

The η^{β} is the adaptive learning rate of parameter β. The equation can be the adaptive rule in order to reduce the output error by adaptively adjusting the connecting strength β.

The time attenuation constant of dynamic threshold controls igniting time interval and it also influences the roughness of the processing image to some extent. Then the adaptive rule of time attenuation constant of dynamic threshold can be obtained as follows:

$$\begin{aligned}\alpha_E^{new}&=\alpha_E^{old}-\eta^{\alpha}(T_{desire}-T_{actual})\frac{\partial T}{\partial\alpha_E}\\&=\alpha_E^{old}-\eta^{\alpha}(T_{desire}-T_{actual})\mathrm{In}(\frac{V_E}{(1+\beta^*L)})(-\frac{1}{\alpha^2})\end{aligned} \quad (16)$$

And the adaptive criterion of dynamic threshold magnitude constant can also be obtained based on the above principles:

$$V_E^{new}=V_E^{old}-\eta^{V}(T_{desire}-T_{actual})\frac{1}{\alpha_E V_E} \quad (17)$$

The above deducted adaptive rules of key parameters can be applied directly to each neuron. Then optimal parameter settings (for desired output of a specific application) can be obtained. These parameters can make the PCNN more effective when it does image processing tasks, while the generalization ability of the network is improved. Each neuron uses different parameters when the firing cycle of each neuron is adjusted.

RESULTS AND DISCUSSION

In order to verify the effectiveness of the algorithm, simulation test is done with the 12-electrode system. Chen *et al*. (2008) have designed and implemented the data acquisition system which is used to obtain data of 12-electrode electrical capacitance tomography. The study also discusses the pipeline grid division method. In this study, pipeline section is divided into 1024 pixels with 32×32 grid when it is reconstructing images. There are 856 imaging units in the effective area of the pipeline section. Wang *et al*. (2010) proposed a novel algorithm which is based on trust region. The algorithm is used to reconstruct image for electrical capacitance tomography system. The study selects typical flow patterns in the simulation experiment. In this study, laminar flow, core flow and bubble flow are selected to test the algorithm in the pre-set experiment. It makes statistics of filter threshold when it is reconstructing image. The system reconstructs images by using pulse coupled neural network and the quality of images will be compared with the other images reconstructed by LBP, Landweber and CG. The simulating calculation is done on a computer with dual-core Pentium 2 CPU and 2G memory by using MATLAB.

The speed of reconstructing image is represented by using iterative number N. The greater is N, the longer is the reconstruction time and this illustrates the speed is slower. The algorithm sets N = 0 because the LBP method belongs to the single step procession. Iterative step number N is determined by numerical experiments. Chen *et al*. (2008) proposed a method which measures parameters of two-phase flow and it can also reconstruct image for electrical capacitance tomography. The equation of iterative error is discussed in the study. The usual practice is that the iterative error should satisfy the following equation:

$$\|SG_k\text{-}C\|<\epsilon \quad (18)$$

Then the iteration is stopped. The space image error is chosen as evaluation index of image quality when the quality of the reconstructed image is analyzed. It is defined as follows:

$$\varepsilon=\frac{\sum_{i=1}^{n} g_{i(img)}-g_{i(init)}|}{\sum_{i=1}^{n} g_{i(init)}} \quad (19)$$

Table 1: Comparison of images which are reconstructed by using different algorithms for 4 different flow patterns

Preset flow(1/3 Laminar flow) | Preset flow(2/3 Laminar flow) | Preset flow(Core flow) | Preset flow (Bubble flow)

Image reconstruction results of LBP algorithm

Image reconstruction results of Landweber algorithm

Image reconstruction results of CG algorithm

Image reconstruction results of the algorithm in this study

Table 2: Errors of images which are reconstructed by using different algorithms for 4 different flow patterns (%)

Algorithm	1/3 laminar flow	2/3 laminar flow	Core flow	Bubble flow
BP	40.32	49.68	86.38	98.71
Landweber	20.16	34.57	45.45	84.61
CG	26.61	38.66	63.63	99.35
Algorithm in this study	18.53	35.16	20.15	46.78

Table 3: The No. of iterations (times) of different algorithms which are used to process 4 different flow patterns

Algorithm	1/3 laminar flow	2/3 laminar flow	Core flow	Bubble flow
LBP	0	0	0	0
Landweber	21	23	15	13
CG	7	9	6	6
Algorithm in this study	40	38	28	20

In the equation: $g_{i(img)}$ represents the reconstructed image vector. $g_{i(init)}$ represents the distribution of media prototype image vector. I represents the index of imaging region dividing unit. n represents the total number of units in imaging area. The experimental results is shown in Table 1 (The black area represents the water and the white area represents transformer oil).

The initial parameters are setted as follows: parameters according to the expected output are setted as: $\beta = 0.20$, $a_E = 0.1$ and $V_E = 20$. The parameters which are needed to adjust before adaptive network operates should be setted as: $\beta = 0.60$, $a_E = 0.80$ and $V_E = 25$ and the other parameter is setted as: $V_L = 1$. The experimental result shows that the convergence rate of PCNN is accelerated obviously after it is trained. The iterative number of the algorithm (adjustment of weights) is more than 100000 times in order to make the MSE network error reduce to 0.026. The training error drops sharply in the first 10000 training cycles but the trend of the decline of the error obviously slows down later.

For core flow and laminar flow, the images which are reconstructed by using this algorithm are closer to the original pattern. The quality of the images is better than that of the images which are reconstructed by other three algorithms. This can be seen obviously from Table 1 and 2. For complex bubbly flow, there is a certain gap between the imaging effect of this algorithm and the original image pattern but it has improved greatly compared with the other three algorithms. Experimental result shows that the iteration steps of CG are the least which can be seen from Table 3, while the iteration steps of this algorithm are more. After above analysis, it is known that for the simple flow pattern and complex pattern, the quality of the images which are reconstructed by using the algorithm in this study is better. In addition, the images are more close to original images compared with these images reconstructed by LBP, CG and Landweber algorithm. But the number of iterations of this algorithm is larger.

CONCLUSION

This study presents a novel image reconstruction algorithm. It is based on pulse coupled neural network (PCNN) and it is used to process different flows in electrical capacitance tomography (ECT). The calculation steps of the algorithm are given after analyzing the basic principles of electrical capacitance tomography and PCNN. This algorithm is used in order to solve nonlinear and ill-posed problems. The values of main parameters of PCNN can be adjusted by applying gradient descent method. And it adjusts the adaptive rate in order to avoid falling into the local minimum problem. The algorithm has the advantages of small imaging error and high imaging precision. It is easy to meet the convergent requirement. Simulation results show that the quality of the images reconstructed by this algorithm is far better than LBP algorithm. In addition, they are also better than the images reconstructed by Landweber and CG and its reconstructed images are closer to the original pattern. So it provides a new and effective method for ECT image reconstruction.

ACKNOWLEDGMENTS

This study is supported by National Natural Science Foundation of China (60572153, 60972127), Higher Education Doctoral Fund (200802140001), Natural Science Foundation of Heilongjiang Province (QC2012C059), Chunhui Plan of Ministry of Education (Z2007-1-15013) and Science and Technology Project of Department of Education in Heilongjiang Province (11541040, 12511097, 12531094).

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