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Research and Application of NSSN Neural Network in Electrical Capacitance Tomography Image Reconstruction

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Abstract

Electrical capacitance tomography (ETC) is a kind of imaging technology which is based on the difference in the sensitivity distribution of capacitance in each medium. In under the background of the ETC system of 12 electrode capacitance sensor arrays an improved NSSN neural network algorithm will be applied to the reconstruction of the image of ECT system in this thesis, and making the ECT image reconstruction algorithm more stable and efficient. In training of the neural network algorithm with large scale, we adopt the method of dividing the sub network to improve it. Through the closed pipeline of gas and solid two-phase flow monitoring data and using the improved neural network image algorithm for image reconstruction. The experimental results show that the improved method makes up for the deficiency of the slow speed of the large scale neural network operation.,simplify the neural network structure, for electrical capacitance tomography provides a new way of thinking.

Keywords: *Electrical capacitance tomography; New NSSN network; Partition sub network; Image reconstruction*

1. Introduction

Electrical capacitance tomography is formed and developed in the late 1980s, it has the advantages of low cost, simple structure, fast response speed, good safety performance, wide application range and so on. In recent years, it has been widely used in many fields, such as chemical industry, petroleum, metallurgy, energy, and so on. Especially in the application of real-time multi-phase flow measurement technology is regarded as one of the most promising process of imaging industry [1].

Image reconstruction algorithm is the key technology in the detection system of electrical capacitance tomography. At present, Image reconstruction algorithm is widely used in industry are mainly linear back projection algorithm (LBP), Landweber iterative method, standard Tikhonov regularization method *etc.*The linear back projection method is characterized by simple algorithm, fast reconstruction, this algorithm has better property of regularization, the image reconstruction of ECT in the more commonly used a kind of iterative algorithm, but the quality of the reconstructed image is not good enough [2].

In this paper, a novel feed-forward neural network algorithm (NSSN) is proposed: In the hidden layer, the use of the similar support functions as the Hidden-Layer of the excitation function, so that the image reconstruction process to solve the stability; For ECT system neurons in hidden layer size larger problems, we puts forward the solution of a sub network, to a complex problem decomposition is related to several sub problems, the sub problem is relatively simple, each sub problem to do a separate neural network module of data processing. The improved NSSN algorithm can improve the quality of

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image reconstruction, and it also improves the speed of network training.

2. Structure and Basic Principle of ETC System

The general structure of electrical capacitance tomography system is shown in Figure 1, which is composed of capacitance sensor, capacitance measurement and data acquisition system, real-time embedded system, communication network and image display system.

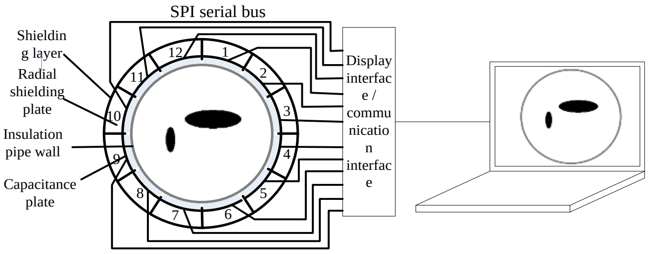


Figure 1. Basic Structure of ECT System

Capacitance sensor of the metal plate is uniformly attached Outside of the insulated pipe wall of the measurement section structure, the pairwise combinations of any two plate formed different electrodes for in the pipe cross section have a different measurement sensitive area. Due to the multiphase fluid the "phase" with different dielectric constants, when the pipeline in multiphase flow fluid composition or flow pattern change, making capacitance sensor on different electrode on the capacitance value change, in all the different electrode of capacitance measurement data obtained will be reflected the views on the cross section of each phase of the number and the distribution. The capacitance measurement and data acquisition circuit are integrated directly into the shielding cover, so that the lead wire between the electrodes is reduced to a few centimeters, which greatly reduces the stray capacitance, and reduces the volume of the system.

The principle of electrical capacitance tomography technology is based on multiphase fluid phase media with different dielectric constant. When the concentration and distribution of change will be caused by multiphase flow mixed body equivalent dielectric constant changes, so that the measured capacitance value is changed. Through the distribution of the multiphase medium and the changes of the concentration, which are reflected by the changes of the capacitance of the array electrode in the pipeline, we rebuild the distribution image which is on the cross-section of the pipeline, extract the characteristic parameters of different medium like concentration, phase holdup and flow patterns and realize the phase distribution visualization of different medium in the pipeline. When the fluid state or composition changes in the pipe, the dielectric constant of the medium is changed [3].

In order to reduce the error between the actual measurement data and the theoretical analysis of the data as much as possible, we put the sensitivity function was also normalized to carry on the analysis, the plate I and J of the normalized capacitance sensitivity field distribution the following definition form [4]:

$$S_{i,j}(t) = \frac{\mu(t)\bullet(C_{i,j}(t)-C_{i,j}(\varepsilon_1))}{C_{i,j}(\varepsilon_3)-C_{i,j}(\varepsilon_1)} \tag{2-1}$$

In the formula, t=1, 2, 3, …Nein, ε_2 and ε_1 is a two-phase flow in the pipeline of the phase of the dielectric constant($\varepsilon_2 \geq \varepsilon_1$), the dielectric constant unit of t is $C_{i,j}(t)$, When the dielectric constant of the other elements is ε, the capacitance between the electrode plates I and J: $C_{i,j}(\varepsilon_2)$ and $C_{i,j}(\varepsilon_1)$ are the capacitance values of I and J, which are filled with dielectric between ε_2 and ε_1; $\mu(t)$ is the reciprocal of the area of the unit of t; Nein is the number of units in the pipeline. This definition of the sensitive field distribution indicates that the unit t unit area of the medium by ε_1 into ε_2 after the plate I and j between the normalized capacitance value change, That is the change of the capacitance normalized value [5].

At present, the number of capacitor plates used in ECT system is 6, 8, 12, 16, In this paper. In this paper, the 12 electrode sensor system is used as the research object, and in order to measure the capacitance value formed by the two combinations of all the plates, these capacitance values are used as projection data onto image reconstruction. In a complete measurement process, the system can scan 66 different angles of the multiphase fluid in the tube, so that the 66 projection data can be obtained. Electrical capacitance tomography is used to obtain the parameters of multiphase flow and image reconstruction by using the projection data [6]. Sensitive field to take the form of triangulation, the split unit is 192, as shown in Figure 2 [7].

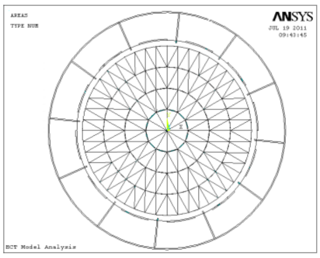


Figure 2. Split Graph of 12 Electrode Capacitance Sensor

3. NSSN Algorithm of ETC System

A new supported set neural network NSSN adopts the three-layer feed-forward neural network structure model. It uses supported set function as the transformation function of the hidden layer unit, and any two output samples are not equal. In this way, we can ensure the inevitable existence of the strictly diagonally dominantly free weight matrix output by the hidden layer, and overcome the BP algorithm's shortcoming of easily trapping into local minimal value. Then, the empirical formula is used to initially establish the network structure with fewer hidden nodes. After that, according to the specific problem to be resolved and the calculation accuracy to be required , we obtain the corresponding minimum error network by constantly adjusting the number of the hidden layer neuron in the network, making the network to meet the practical needs [8].

3.1. Neural Network

Neural network is a distributed information processing structure, the main character is parallel, it is a network which is composed of a processing unit which is connected with each other through a unidirectional signal path, the processing unit not only has local storage function, also with the implementation of local information processing capability, artificial neural network in many areas of artificial intelligence, pattern recognition, and control made great achievements.

3.1.1. Neuron Model: Artificial neural network system is composed of a lot of neurons, which is the basic unit of the neural network, the model is shown in Figure 3, a neuron model can be divided into the following three elements [9]:

1. A set of weights are connected, and their weights are positive, which indicates that the current neurons are activated and their weights are negative, which indicates that the current neurons are suppressed;

2. A weighted sum cell for each input signal;

3. A nonlinear activation function, the main function of the effect is to carry out nonlinear mapping and limit the output range of neurons.

In addition, there is a threshold to control the output θ_k , the neuron model is expressed as:

$$x_k = \sum_{j-1}^{m} w_{kj} x_j ; v_k = net_k = x_k - \theta_k ; y_k = \varphi(v_k) \quad (3\text{-}1)$$

Formula: $w_{k1}, w_{k2},..., w_{km}$ is the k-th neuron connection weights; $x_1, x_2, \ldots, x_m$ is input value; θ_k is threshold; y_k is the output of the k-th neuron; $\varphi(v_k)$ is a linear combination of functions, generally has a piecewise function, *sigmoid* function, step function and other functions.

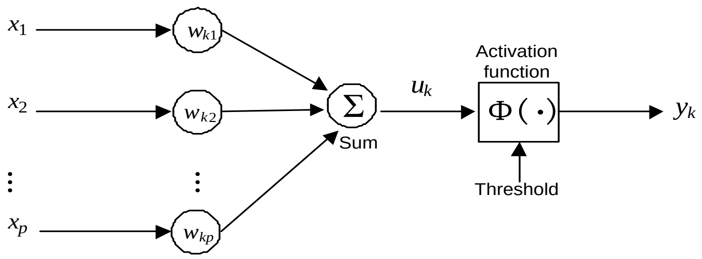


Figure 3. Basic Neural Model

3.1.2. Neural Network Architecture: In addition to the characteristics of neurons, the topology of the network is also an important feature of the neural network. From the point of view of the internal information transmission in the neural network, the neural network can be divided into two types: the feed forward neural network and the feedback types neural network [10].

Feed-forward neural networks can be divided into the input layer, the hidden layer and the output layer. The nodes of input layer and output layer are connected with the outside world, and the other middle layer is called the hidden layer. In the information network, feed-forward refers to the information transmitting process, from input layer to hidden layer to output layer processing. Network nodes are divided into two categories: A class is the input node, it is mainly from the outside to receive information and forward to the hidden layer; The other is a node that has processing power, which includes the hidden layer and the output layer node. The output from the one layer of feed-forward neural network forms the input to the next layer, and the information is processed by layer by layer, there is no feedback loop, so it is easy to establish a multi-layer feed-forward network.All of the feedback node type neural network has the function of information processing, each node can receive input and output to the outside world [11].

Above to describe the structure and information flow of the network is a summary of the common network structure, in the practical application of the neural network it can have more than one or several forms, Specific can be divided into: feed forward, Input and output of feed-forward with feedback hierarchical, interconnection in the feed-forward layer type, local interconnect feedback type, and so on. In the development process of the artificial neural network, we formed the different neural network models of biological neural systems from different angles and levels of description and simulation, which is typical of the neural network have perception neural network, linear neural network, BP network, diameter to basis function network, self-organization network and feedback network [12].

3.2. The Structure and Basic Principle of NSSN Network

In this system, we use the three layers feed-forward neural network based on the class support function to reconstruct the image of the 12 electrode ECT system. NSSN network structure as shown in Figure 4, The input vector of the network is 66 measured capacitance values, the output vector is the gray value of 716 pixels. In the training phase of the network, we use the empirical formula to determine the less hidden nodes to train the network, then, according to the specific problems to be processed and calculation accuracy to be required, we adjust the number of hidden layer neuron network constantly to obtain a suitable network structure, and finally select the number of corresponding hidden nodes when the network gets minimum error.

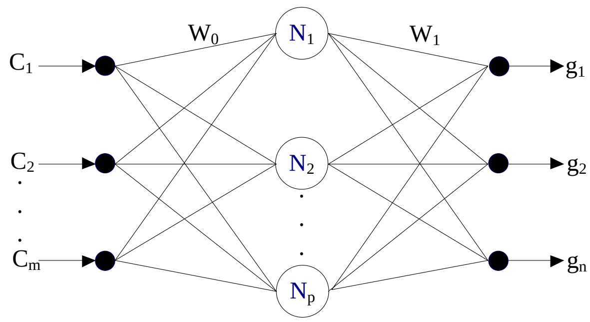


Figure 4. NSSN Network Structure Diagram

The relationship between the input and output layer of the neural network use the identity transform relationship. The relationship between input and output three layers feed-forward neural network as shown in (3-2):

$$\begin{cases} G_0 = C_0 \\ C_1 = W_0^T G_0 \\ G_1 = f(C_1) \\ C_2 = W_1^T G_1 \\ G_2 = C_2 \end{cases} \tag{3-2}$$

Of those, C_0, C_1, C_2 is respectively the input sample matrix, the hidden layer input matrix and the input matrix of the output layer; G_0, G_1, G_2 respectively is the output matrix of the input layer transformation, the actual output matrix of the hidden layer and the actual output of the network; W_0, W_1 is respectively the weight matrix between the input layer and the hidden layer, and the weight matrix between the hidden layer and the output layer.

Assuming that the training samples are not the same, the purpose of network training is to seek the appropriate weights W_0, W_1, which is making the following mapping was established:

$$F : C_0 \to G \tag{3-3}$$

(G as the target matrix.)

3.3. The Determination of the Number of Hidden Layer Neurons and the Excitation Function

Hidden layer neuron activation function and free weights selection is difficult and inappropriate choices will make matrices rather ill, in order to reduce the ill conditioning of the matrix and the computational performance is good, it can be constructed strictly diagonally dominant matrices.

3.3.1. To Determine the Hidden Layer Activation Function: If the three layer feed-forward neural network hidden layer activation function f is $x = c$'s support function, and assume that the input and any sample in two are not equal to each other, there must be a free weight W_0 makes the hidden layer output matrix G_1 strictly diagonally dominant [13]. Therefore, when the selection function of the hidden layer neurons is the support function, we can construct a matrix into a strictly diagonally dominant. There are many functions to meet the above definition, they can achieve zero cost function and accurate mapping functions on the f relaxed the requirements at this point also reflects the NSSN algorithm than BP (request function f Guide) and other traditional algorithms have more extensive application. Here is a selection of Delta function (defined in this paper meet the support function) for the hidden layer activation function.

Delta function:

$$Delta(x;\varepsilon,c)=\frac{1}{\pi}\frac{\varepsilon}{(x-c)^2+\varepsilon^2} \tag{3-4}$$

For the scale of problems have been identified (this article refers to the neural network hidden layer neuron number), using a set of neural network algorithm than traditional BP algorithm in terms of computational accuracy and computational efficiency is significantly improved, Table 1, for the use of MATLAB for the experimental results of 2000 times of iteration.

Table 1. A Set of Neural Network Algorithm and BP Algorithm in Accuracy and Efficiency of the Comparison Table

Scale	BP algorithm		NSSN network algorithm	
	Accuracy($\times 10^{-32}$)speed/s		Accuracy($\times 10^{-32}$)speed/s	
10	0.02	10.4	6.03	0.1
20	0.06	22.3	29.50	1.3
40	0.35	43.7	340.30	12.0
80	1.12	113.5	1038.60	45.2

The experiment proves that the supported set function can realize the hidden layer output matrix is a strictly diagonally dominant, and enhances the anti-interference ability of the network. When the network scale, compared with the traditional BP algorithms, the accuracy and efficiency are improved.

3.3.2. Determination of Hidden Neurons: Two methods are adopted to determine the number of hidden layer neurons have a proper network structure:

(1) Before starting the establishment of the forward network model in the network, hidden layer neural number is determined according to the empirical formula [14]:

$$m \le \sqrt{N*(l+3)}+1 \tag{3-5}$$

Among them, M is the number of neurons in hidden layer, N is the number of input neurons, l is the number of neurons in the output layer. The network is trained. After the end of the training, through the method of correlation analysis method of gray correlation [15] analysis or the output of the hidden layer neurons by correlation analysis between each other, to be combined according to the results of the analysis will be a high degree of correlation of two neurons. Thus, by reducing the number of hidden neurons constitute a new network structure. The new network is trained until the elimination of redundancy of hidden neurons are the best network structure.

(2)Different from the above calculation is the number of neurons in hidden layer to select fewer network models which is trained at the beginning to establish a feed-forward neural network model. After the training, we need to calculate the accuracy of observation network can meet the specific requirements, if able to meet the requirements, determine the structure of the network, or by adding network hidden layer neurons constitute a new network on the new network to continue training.

3.4. Step NSSN Neural Network Algorithm

The NSSN algorithm is mainly composed of two parts: network training and imaging. The algorithm steps are as follows:

(1) Determine the NSSN network structure: input, output and hidden layer nodes number (it were used to gradually reduce the number of neurons in the hidden layer and step wise addition of neurons in the hidden layer is a two way);

(2) According to a certain way of free choice of weights W_0 and initialize the threshold.

(3) The collected data were normalized;

(4) The samples (C, G) provide to the network;

(5) The actual calculation of the hidden layer output matrix G_0;

(6) Calculate the weight matrix W_1 between hidden layer and output layer;

(7) Through the correlation analysis to the outputs of the hidden neurons by correlation analysis between each other, adjust the number of hidden neurons based on the analysis of the results until get the best network structure;

(8) The use of network and trained to detect data for image reconstruction.

In this paper, the use of cement blocks of different shapes and sizes were placed in different positions in the pipeline has been measured data for image reconstruction. The dielectric constant of the air is higher than that of cement, so we set corresponding to the cement of low dielectric constant of the target output value is 1. Air the corresponding target output value is 0. According to the experiment output threshold is 3.5.

3.5. Improved NSSN Algorithm

In the process of image reconstruction for ECT system, the following problems are discovered: this system adopts the neural network of input and output of the number of neurons in large scale, the network training speed is slow. In additions the observed data showed that when the cement block placed measured in different positions of the pipeline data gap is obvious. There is large and uneven distribution of local measurement data values.

According to the phenomenon that, as in the ECT system the sensitivity distribution is not uniform: closer to the pipeline or wall closer to the electrode sensitivity is higher, while in the central region of the imaging sensitivity is low. In order to improve the quality of image reconstruction is necessary to improve the original algorithm, the specific measures are as follows: Based on 12 electrode capacitance sensor with six different sensitive field distribution, the entire pipe section is divided between six regions respectively imaging and then syntheses, that is the whole NSSN network was divided between six subsystems, each subsystem is composed by a homogeneous distribution of the sensitivity field sub network [16].

Contains six subsystems of improved NSSN network in typical sensitive field as shown in Figure 5.

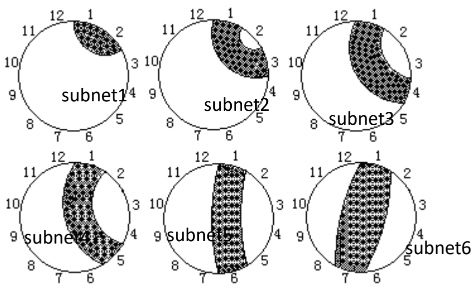


Figure 5. Sketch Map of Sub Network

In the Figure 5, subnets in 1 isomorphic sub network composed of 1 subsystem. Similarly, as well as the subsystem of 2-6.

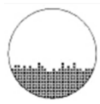
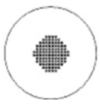
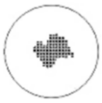
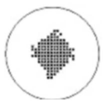
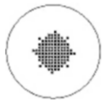
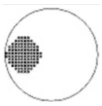
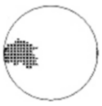
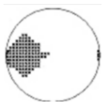
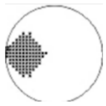
The original network used above six after the division of the input data, each sub network scale has been effectively controlled. In view of the experimental data shows that a large number of adjacent plates and separated by a plate electrode capacitance measured by capacitance value is much higher than the other values between the plates, so the input partitioning the network into two kinds: Subnet 3~6 all the 1/6 of the original data as input data for each subnet, subnet and the 1 and 2 only with the adjacent and separated by a plate all capacitance value as its input data. Then, the method of combining the hidden layer neuron is used to simplify the sub networks, and finally get a reasonable network structure.

The experimental results show that the improved network algorithm not only greatly simplifies the training speed of the network, but also improves the quality of image reconstruction.

4. Simulation Experiment Result Analysis

In this paper, the original NSSN neural network system input data is large,and the training speed is slow and the imaging quality is improved. The total number of samples is 400, the pixels in the imaging area are 716, and the network is divided into six sub networks. Hidden layer excitation function using $Delta(x;0.1,0)$ function, the threshold value is 3.5, higher than 3.5 is air, less than 3.5 is cement. In order to make the input components with relatively equal importance in the process of imaging, the input data are normalized, so that it is in the range of [0, 1]. The reconstruction image is represented by two values. The experimental results are shown in Table 2, the black image area represents the air, and the white image area represents the cement.

Table 2. Image Reconstruction Results

	Target image	BP network image reconstruction	NSSN network image reconstruction	New NSSN network image reconstruction
Laminar flow				
Kernel Streaming				
Eccentric flow				

5. Conclusion

The experimental results show that: the improved NSSN neural network algorithm in the training speed, image quality and other aspects are significantly improved, especially in the flow pattern identification is significantly improved. For examples, Figure 4 shows the eccentric flow than the original NSSN algorithm and BP algorithm to determine the flow regime range has made great progress.

On the basis of the existing algorithm, it will be refined into the recognizable NSSN algorithm based on the flow pattern if he number of samples is increased, which can further improve the accuracy of the reconstruction image and the generalization ability of the network and make the ECT image reconstruction system to achieve the goal of recognizing the flow pattern accurately. So it can be said that the improved NSSN neural network algorithm provides a new and effective method for image reconstruction of electrical capacitance tomography system.

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