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A Noise Reducing Algorithm Based on Pulse Coupled Neural Network Time Matrix for Electrical Capacitance Tomography

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Abstract: The image produced by the reconstruction algorithm for electrical capacitance tomography can be inevitably affected by the outside disturbance and it is destructed in the process of obtaining and transmission. So, the images are affected by noise pollution and the feature extraction and image recognition of subsequent processing of the images are also influenced. In order to solve this problem, a noise reducing algorithm for Electrical Capacitance Tomography (ECT) is presented. It is based on the analysis of the basic principle of electrical capacitance tomography and Pulse Coupled Neural Network (PCNN). The time matrix is the mapping from spatial image information to time information generated by PCNN and the time matrix contains useful information related to spatial information in image processing. The calculation steps for noise reducing are deduced. The size of filter window and the number of filtering can be automatically selected according to the noise intensity. Experiment and simulation results indicate that through analyzing and processing the PCNN time matrix, the image which is polluted by impulsive noise can be filtered efficiently. The effect of reducing impulsive noise of images is significantly better than the median filter, mean filter and wiener filter. This algorithm presents higher peak signal-to-noise and it has better capability to reduce noise. It can also well protect edges and details of images and it is more adaptive.

Key words: Electrical capacitance tomography, noise reducing, time matrix, impulsive noise

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 (Chen *et al*., 2008) and so on. But when the image is being transmitted and processed, the image is inevitably affected by noise pollution in the process of acquisition and transmission because of the outside disturbance and destruction. The noise has a great influence on the subsequent processing of the image. Impulse noise widely exists in the actual image system and the brightness value of impulse noise point is significantly different from the values of other neighborhood image pixels. The formation of black and white bright points in the image greatly influences the image quality and it also influences the image segmentation, feature extraction, image analysis (Wang and Yu, 1995), image recognition and other tasks in the future. Thus, reducing impulse noise is a very important task of image processing.

The median filtering, average filtering and wiener filtering are the traditional filtering methods which are most widely used to reduce impulse noise. The median filter treats all image pixels in the same way, but it does not distinguish noise and non-noise points. So, it will damage and lose the details information of the image whose size is smaller than filtering window, such as edges, corners and so on. Median filter would make the image edge blur. The filter capacity declines quickly when the noise increases. The effect of removing impulse noise by using wiener filter algorithm is also not ideal. In order to overcome above disadvantages, in recent years, some scholars put forward many new methods. The median filter has been improved. The noise pixel is recognized firstly and only the noise pixel is filtered. While the image pixel which is not polluted is invariant, the edge and detail information of images can be better retained. Pitas proposes standard median filter "SMF" (Pitas and Venetsanopoulos, 1992). SMF treates all the image pixels in the same way, but it do not distinguish the non-noise and noise. Therefore, it can not well preserve the edges

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and details of the image. Zhang proposes convolution-based impulse detector and switching median filter (CD-SMF) (Zhang and Karim, 2002). CD-SMF judges whether the target pixel is noise according to the threshold. If the pixel is polluted, then it will remove the noise. Srinivasan proposes Decision-Based filter Algorithm (DBA) (Srinivasan and Ebenezer, 2007), DBA firstly identifies the image pixels which are corrupted by impulse noise, then it treats the noise pixels by using windows matrix. Eng and Ma propose noise adaptive soft-switching median filter (Eng and Ma, 2001), it is more suitable to reduce noise for two value images.

But filtering performance of above mentioned algorithms will decline when the noise strength increases. In order to solve this problem, a noise reducing algorithm based on pulse coupled neural network time matrix for electrical capacitance is proposed according to the characteristics of impulse noise. The algorithm can make the image spatial information mapped to two-dimensional ignition time matrix by using the PCNN cycle igniting. The algorithm can automatically select the size of filter window and the number of filtering according to the noise intensity. The impulse noise can be effectively filtered by using PCNN time matrix. Through the simulation experiment, the algorithm can effectively remove impulse noise. The effect is obviously better than median filter, mean filter and wiener filter. This algorithm has the features of high peak signal-to-noise ratio and it can well protect the edge and detail information of the image. When the noise strength increases, the adaptability of filtering noise is also good. The performance of reducing noise is greatly better than the median filter, mean filter and wiener filter.

MATERIALS AND METHODS

Basic principles of electrical capacitance tomography system: Basic principle of electrical capacitance tomography system: The working principle of electrical capacitance tomography system is that installing capacitive sensor array around the measured field (Chen *et al*., 2009). When the concentration or distribution of the medium changes, the sensor will detect the changes of capacitances values and transmit them to the computer to process. Then, the computer will reconstruct the distribution of the medium section and calculate the flow parameters of multiphase flow (Van Gemert *et al*., 2009). ECT Electrical Capacitance Tomography (ECT) system is mainly composed of capacitor sensors, data acquisition system and the computer which is responsible for reconstructing images (Ge and Song, 2010). The physical structure of ECT is shown in Fig. 1.

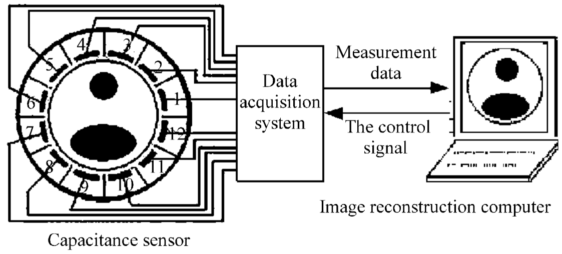


Fig. 1: Structure of electrical capacitance tomography (ECT) system with 12-electrode

At present, most of the ECT image reconstruction algorithm is based on the linear model. In the model, the dielectric constant is mapped to the capacitor (Chen *et al*., 2003). After discretization, linearization and normalization, the model can be expressed as:

$$C = S\varepsilon \qquad (1)$$

In the equation, $C \in R^m$ represents the capacitance measurement value, $S \in R^{m\times n}$ represents the coefficient matrix (sensitivity matrix) and $\epsilon \in R^n$ 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 (Wang, 2007) of ECT system is to reconstruct medium dielectric constant distribution map in the detection zone by observing and measuring the capacitance measurement values (Chen *et al*., 2007). That is to solve the gray values of each pixel in the imaging area.

PRINCIPLE OF ADAPTIVE PULSE COUPLED NEURAL NETWORK

Principle of adaptive pulse coupled neural network: PCNN is also known as the third generation artificial neural network. It is the feedback network inspired by biological visual cortex model and it is composed of a number of interconnecting neurons. Generally, each neuron of PCNN is composed of three parts: Input section, connecting part (modulation section) and pulse generating part (Wang and Lin, 1997). Single neuron model is shown in Fig. 2.

Discrete mathematics equations of pulse coupled neural network for reconstructing image are described as below:

$$F_{ij}[n] = \exp(-a_F)F_{ij}[n-1] + V_F\sum M_{ijkl}Y_{kl}[n-1] + P_{ij} \qquad (2)$$

$$L_{ij}[n] = \exp(-a_L)L_{ij}[n-1] + V_L\sum M_{ijkl}Y_{kl}[n-1] \qquad (3)$$

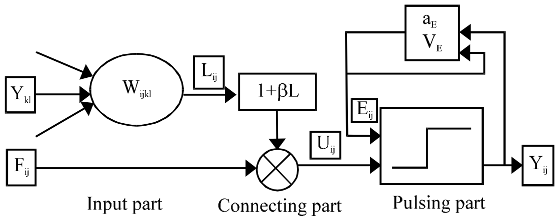


Fig. 2: Single neuron model of simplified pulse-coupled neural network

$$U_{ij}[n] = F_{ij}[n](1+\beta L_{ij}[n]) \tag{4}$$

$$E_{ij}[n] = \exp(-a_E)E_{ij}[n-1] + V_E \sum Y_{ij}[n]) \tag{5}$$

$$\begin{cases} Y_{ij}[n]=1, U_{ij}[n]\rangle E_{ij}[n] \\ Y_{ij}[n]=0, \text{otherwise} \end{cases} \tag{6}$$

The subscript ij represents neuronal labeling. In the formula, F_{ij}, L_{ij}, U_{ij} and E_{ij} respectively represent external stimulation feedback input, connecting input, internal activities and dynamic threshold of the neurons (Chacon *et al*., 2002). The external excitation forcibly excited by neurons is image pixel gray value P_{ij}. In the formula, M and W represent connection weight matrixes (generally W = M) and V_F, V_L and V_E, respectively represent amplification factors. Time decaying constants are respectively represented by using α_F, α_L and α_E. n represents the iteration number (Stewart *et al*., 2002). In the formula, Y_{ij} represents two values output and that is the image pixel gray value.

The model is simplified and improved based on traditional PCNN in order to overcome the shortcomings: Too many artificial multiple parameters, poor adaptability and repeated declining index (Stewart *et al*., 2002). The improved discrete mathematics equations are described as below:

$$F_{ij}[n] = I_{ij} \tag{7}$$

$$\begin{cases} L_{ij}[n]=1, \sum\limits_{i,j\in W} Y_{ij}[n]\rangle 0 \\ L_{ij}[n]=0, \text{otherwise} \end{cases} \tag{8}$$

$$U_{ij}[n] = F_{ij}[n](1+\beta L_{ij}[n]) \tag{9}$$

$$E_{ij}[n] = \exp(-a_E)E_{ij}[n-1] \tag{10}$$

$$\begin{cases} Y_{ij}[n]=1, U_{ij}[n]\rangle E_{ij}[n] \\ Y_{ij}[n]=0, \text{otherwise} \end{cases} \tag{11}$$

Linking strength β_{ij} is selected as below in order to process the impulse noise image:

$$\begin{cases} \beta_{ij}[n]=\max\limits_{K,l\in W} Y_{ij}\left[\sigma_W \big/ \sigma_W (I_{ij}-I_{Kl})^2+1\right], Y_{kl}[n]=1 \\ \beta_{ij}[n]=0, \text{otherwise} \end{cases} \tag{12}$$

In the equation, σ_w is image local variance of the W window.

SIMPLIFIED PCNN TIMED MATRIX IMAGE ALGORITHM FOR NOISE REDUCING

Simplified pulse coupled neural network timed matrix image algorithm for noise reducing: Impulse noise is very characteristic. In general, gray pixel values of noise image (He and Li, 2002) and the surrounding pixel values are not the same, especially when the image is disturbed by extreme impulse noise. This feature is more obvious when the image which has limited grayscale is contaminated by certain intensity pulse noise. It can lead some of the pixel gray value to be maximum or minimum. Therefore, before filtering the image, the image whose pixels are above (or below) the given pixel gray value (these pixels are not necessarily all noise pixel) is advanced pretreated for the correction of the gray value (Wang *et al*., 2010). Then it can be more suitable for subsequent processing. The algorithm which is used to make sure the accurate position of noise is proposed on PCNN after image preprocessing and it only chooses the noise pixel to be filtered.

Fixed position of noise pixel: When the algorithm processes the image by using simplified and improved network model, it is a single two-dimensional connectionless network. The number of the neuron is equal to number of the input pixels in the image. And they are corresponding to each other. In this study, gray value of each pixel which is polluted by noise in the pretreatment image is inputted into the corresponding neurons of PCNN simplified model. The simplified and improved network model operates until all of the neurons are firing. Then the algorithm can get the time matrix T which records primary igniting time of each neuron and it can reflect the time domain information of the image based on spatial information. It is spatial structure of the image mapped to the time series. The formulas of ignition time are described as follows:

$$\begin{cases} T_{ij}[n]=N, Y_{ij}[n]=1 \\ T_{ij}[n]=T_{ij}[n-1], \text{otherwise} \end{cases} \tag{13}$$

By using the monotone threshold function whose index decreases in PCNN, the elements with smaller value in the formed time matrix is corresponding to pixels with larger gray value in the noisy image. The noise makes the ignition time of neurons delay or advance. The algorithm slides a (2m+1)×(2m+1) window matrix K whose values are all 1 to identify the firing time values of neurons. And the (2m+1)×(2m+1) elements are sorted to form a vector U. If the value corresponding to the intermediate position of vector U is maximum or minimum, then it is the noise that makes ignition time of neurons delay or advance. The algorithm can judge that the pixels in the preprocessing image which are corresponding to center elements of time matrix T are the noise pixels. Thus noises can be fixed a position.

Automatic selection of filter window and filtering times: In order to effectively reduce the noise and improve the quality of image, self-organization conversion of the neuronal connections and filter frequency in PCNN network can be automatic selected according to the estimated value of noise intensity.

Impulse noise only appears in the pixel whose gray value is 0 or 1. If the algorithm only counts these pixels, then the pixel with value 0 or 1 in the image may also be used as a noise to statistics. In order to avoid the misjudgement, the algorithm uses a h×h child window $W_{h\times h}$ with the central investigated pixel (i,j). If the gray value of pixel (i,j) is 0 or 1 and there are no pixels whose gray value is between 0 to 1, then the pixel dot is considered not to be contaminated, or it is counted as noise pixel. In the image, all of polluted points which are considered to be polluted are added up together and it is divided by the number of pixels of the image. Finally the result can be used as an estimate of the noise intensity N_Y. After a large number of simulation experiments, the algorithm selects the square filter windows H. The size of the window is h×h. It is according to the following rules:

$$\begin{cases} h = 3, 1 \le N_Y \le 2 \\ h = 5, 3 \le N_Y \le 5 \\ h = 7, 6 \le N_Y \le 8 \\ \text{others}, N_Y = 9 \end{cases} \tag{14}$$

If the noise density is high, then the image needs multiple filtrations. In certain strength of noise, PSNR firstly increases with the increase of the number of filtering. The best Peak Signal-to-Noise Ratio (PSNR) can be gotten after optimal filtering frequency, but the PSNR is no longer increasing with the increase of the filtering times of filtered image. The relationship between number N and the intensity of noise filtering N_Y is putted forward by using data fitting method:

$$N = \text{ceil}(\exp(2.75 \times N_Y)) \tag{15}$$

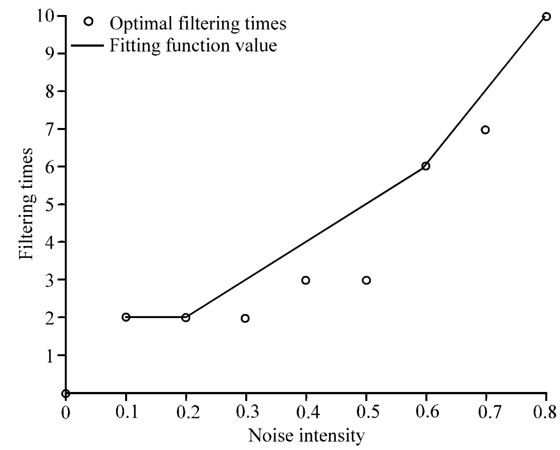


Fig. 3: Optimal filtering times and the number of filtering which is gotten by fitting when the noise intensity changes from 10-80%

The Ceil (x) is the least integer operation and the result is no less than x. Figure 3 is the image which shows the comparison of filtering times (solid line) and the number of optimal filtering (DOT) when the noise intensity changes from 10-80%. There are four points which show optimal filtering times and the actual filtering times are the same in the figure and its value is on the fitting curve. The other four points of optimal filtering times are not on the curve fitting, but they are below the fitting curve. That is the ideal filter frequency value is less than the actual value of the filtering times.

ALGORITHM STEPS

- Input the electrical capacitance tomography image 1 (i, j) which contains impulse noise
- Preprocess the image 1 (i, j) and form the preprocessing image:
  - The algorithm compares 1 (i, j) with the threshold ΔE, if 1 (i, j)<ΔE, then the preprocessing image 1_1 (i, j) = ΔE, or go to (b)
  - If 1 (i, j)ΔE, then 1_1(i, j) = L-ΔE, or 1_1 (i, j) = 1 (i, j) (where L is the maximum gray level of the image)
- Initialize feedback input F, threshold E, output Y, connecting input L and cycle times, N = 5, β = 0.00, ∂_E = 0.01 and V_E = 0. Establish neuron output state table of PCNN, initial output state of each neuron is flameout, that is Y_{ij} = 0
- The statistics of noise intensity: initialize the number of pollution points sum = 0, for each pixel (i, j), if x (i, j) = 1 or 0, x (m,n)∈(0,1) and x (m,n)∈$W_{h\times h}$, then

x (i, j) is polluted and add 1 to the value of sum. Calculation formula of noise intensity is: Sum/P×Q, P and Q represent the width and height of the image. When the algorithm does the statistics of noise intensity of electrical capacitance tomography image, the diameter of reconstructed image is the length of edge and the image is extended into a square in order to be counted. According to the Eq. 14, 15, the algorithm determines the size of the filter window H and filtering times N and it can automatically select neuronal connection mode of the PCNN network

- Calculate U_{ij} according to the Eq. 8, 9 and 12
- Calculate E_{ij} according to the Eq. 10
- The algorithm determines whether the corresponding neurons are firing according to the Eq. 11, if the neuron is igniting, then mark the corresponding position in the output state table. And calculate its ignition in order to judge whether the neuron make other near neurons also ignite
- If N≠0, iterate the Eq. 7-13 for the image, get the time matrix T and make sure that the neurons are all firing
- Mask T with all 1 windows matrix K with the size h×h and sort elements in order to produce the vector U
- Determine the kinds of the filtering method by using the time matrix T and the generated vector U:
    - If all elements of U are equal and equal to the elements of T(i, j), then algorithm uses the mean filter for the elements which is around the central element S (i, j)
    - If the maximum or minimum element in the U is not equal to T (i, j), then directly output S (i, j)
    - Use h×h median filtering method to all of the elements which are around the central element S (i, j)
- If all the elements in the T did not finish processing, go to (7), otherwise, output the filtered image

RESULTS AND DISCUSSION

In order to verify the effectiveness of the algorithm, simulation test is done with the 12 electrode system. Pipeline section is divided into 1024 pixels with 32×32 grid when it is imaging. There are 856 imaging units (Yang, 1997) in the effect area of the pipeline section. The typical flow pattern: Laminar flow, core flow and trickle flow are done with the pre-set experiment. It makes statistics of filter threshold (Mahvash and Ross, 2008) when it is reconstructing the image. The original image is pulsed, respectively with 10-80% different strength of impulse noise and the algorithm in this study is tested. The effect of reducing noise with median filter, mean filter and wiener filtering is to be compared. The simulating compute is done on a computer with dual-core Pentium 2 CPU and 2G memory by using MATLAB. In this study, assessment rules of the quality of images are the Peak Signal-to-Noise Ratio (PSNR), mean Square Error (MSE), Mean Absolute Error (MAE), improvement factor of signal-to-noise ratio (ISNR) and other evaluation indexes. These assessment indexes are defined as follows:

$$\mathrm{PSNR} = 10\mathrm{Lg}\frac{\frac{1}{M\times N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(A(i,j)-C(i,j))^2}{\frac{1}{M\times N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(B(i,j)-C(i,j))^2} \tag{16}$$

$$\mathrm{ISNR} = 10\mathrm{Lg}\frac{255^2}{\frac{1}{M\times N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(C(i,j)-A(i,j))^2} \tag{17}$$

The equation of mean square error (MSE) and the Mean Absolute Error (MAE) are defined as follows:

$$\mathrm{MSE} = \frac{1}{M\times N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(C(i,j)-A(i,j))^2 \tag{18}$$

$$\mathrm{MAE} = \frac{1}{M\times N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left|C(i,j)-A(i,j)\right| \tag{19}$$

In the equation, M and N, respectively represent the width and height of the image. In addition, A(i, j) represents filtering image, B(i, j) represents the image with noise and C(i, j) represents the standard image. The improvement factor of signal-to-noise ratio (ISNR) represents the degree of suppressing the noise and it is better if its value is lower. PSNR represents the fidelity of original image and it is better if its value is greater. The smaller of the value of MSE and MAE, the more useful original information of the noise image after filtering is retained. It is more obvious of the effect of protecting the edges and details and its filtering effect is better.

In the experiments, the algorithm firstly pre-processes the noisy image. Then it counts the information of noise intensity and it analyses pulse coupled time matrix of the noise image. Finally it classifies the image and respectively processes the image by using the mean filter and median filter. The method proposed in this study can be adaptive. It can automatically select the PCNN filtering times and change the connection mode of neurons according to the noisy intensity. It also reduces the subjective factors which can influence the assessment. So it prevents noise image to be fuzzy because of smoothing and filtering too many times by using PCNN.

Table 1 are the obtained filtering results of different flow patterns with noise by using different filtering

Table 1: Filtering results of the images which are contaminated by impulse noise with different flow patterns by using different filtering algorithms

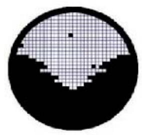
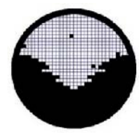
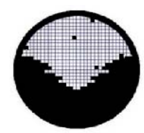
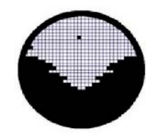
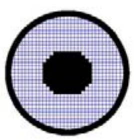
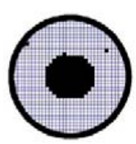
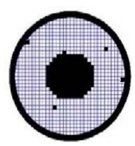
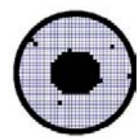
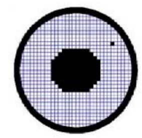
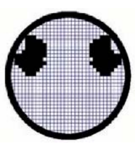
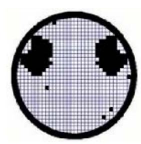
Original image	Median filter algorithm	Mean filter algorithm	Wiener filtering algorithm	Algorithm of this study
Filtering results of obtained 2/3 laminar flow which is reconstructed by LBPlinear back projection algorithms(LBP) and added 10% noise by using different filtering algorithm				
Original image	Median filter algorithm	Mean filter algorithm	Wiener filtering algorithm	Algorithm of this study
				
Filtering results of obtained core flow which is reconstructed by Conjugate Gradient (CG) and added 40% noise by using different filtering algorithm				
Original image	Median filter algorithm	Mean filter algorithm	Wiener filtering algorithm	Algorithm of this study
				
Filtering results of obtained trickle flow which is reconstructed by Landweber and added 60% noise by using different filtering algorithm				
Original image	Median filter algorithm	Mean filter algorithm	Wiener filtering algorithm	Algorithm of this study
				

Table 2: Comparison of experimental data PSNR Peak Signal-to-Noise Ratio (PSNR) of laminar flow filtering image which is added noise of different intensity by using different kinds of algorithms

Intensity of noise (%)	Median filter algorithm	Mean filter algorithm	Wiener filtering algorithm	Algorithm of this study
10	29.17	24.19	22.43	35.78
20	26.65	21.68	20.59	34.83
30	23.77	18.57	19.17	33.75
40	20.82	15.42	17.36	32.62
50	18.26	12.39	15.49	31.58
60	16.49	9.86	13.51	30.98
70	14.57	7.13	11.37	30.27
80	11.69	4.05	8.52	29.93

Table 3: Experimental data of PSNR, MSE, MAE, peak signal-to-noise ratio (PSNR), mean square error (MSE), mean absolute error (MAE) and ISNR improvement factor of signal-to-noise ratio (ISNR) of laminar flow image which is added 60% noise by using 4 different filtering algorithms

	Filtering method			
Index value	PSNR	MSE	MAE	ISNR
Image with noise	16.49	1561.22	13.47	—6.87
Median filter algorithm	30.02	81.53	4.11	—8.53
Mean filter algorithm	24.11	412.36	13.39	—7.76
Wiener filtering algorithm	19.75	876.36	14.76	—9.95
Algorithm of this study	32.34	51.85	2.68	—15.93

algorithm (Linear Back Projection algorithm (LBP), Conjugate Gradient algorithm (CG) and Landweber algorithm) (Yang *et al*., 1999). Through the comparison, the algorithm of this study not only has the better ability of reducing the noise than the median, mean and wiener filtering, but also it can well protect the edges and details of the image. Simplified PCNN model has relatively smaller data than the traditional model and it has less running time. It is in favor of the real-time image signal processing. So, the mode can be more suitable for the real-time signal processing of the image.

In order to get the further validation of the algorithm proposed in this study, it is compared with the traditional filtering method. Table 2 is the comparison of PSNR values gotten by using various algorithms when noise intensity is different. PSNR values of algorithm proposed in this study were all higher than the values of classical filtering algorithm. Especially when the noise intensity is high, such as the strength is higher than 50%. It shows that the filtering effect is better than other filtering algorithms. Table 3 shows numerical evaluation of different algorithms of laminar flow added 60% noise. Compared with the traditional filtering methods, the algorithm can get high PSNR values and small MSE values, MAE values and ISNR values. The result shows that although the strength of the noise is great, the degree of inhibition of noise image is still very high and it has a very good filter effect.

After the comparison and analysis of subjective and objective factors of above experimental results, it can be known that when image is polluted by different degrees of noise, the filter algorithm proposed in this study is better than the traditional filtering methods, such as mean filtering, median filtering and Wiener filtering algorithm. Not only the effect of the noise reducing is good, but also it can well protect the edge details of image. So, the quality of the image is much better than others.

CONCLUSION

This study proposes a noise reducing algorithm of electrical capacitance tomography image based on coupled neural network (PCNN) timed matrix. PCNN has ignition capture ability and it can make the neighborhood points whose gray value is less different ignite. It can remove the noise of the image. At the same time it also can well reserve the detail information. But it will not make the image fuzzy. It realizes the automatic selection of the conversion of neuronal connections mode and the adaptive filtration in PCNN by counting the noise intensity. This can reduce the influence of subjective factors of the effect on removing noise. So, the method has the characteristics of strong adaptability and good effect on noise reducing. The simulation results show that the effect of noise reducing by using this algorithm is far better than the median filter, mean filter and wiener filter. So, it provides a new method to reduce the noise for ECT.

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