Simulation of Neural Network-Multicriterion Optimization Image Reconstruction Technique (NN-MOIRT) for imaging using a 32-channel Brain ECVT sensor

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Abstract. NN-MOIRT has been proposed earlier as an alternative for existing image reconstruction algorithms that can accurately show a volumetric image in a cylindrical sensor vessel. The Brain ECVT sensor has a different shape and dimensions compared with a common ECVT sensor, which has a cylindrical shape. Using a different sensor changes the image reconstruction algorithm parameters. Thus, the image reconstruction algorithm should be modified to be able to properly make a reconstruction. In this study, a simulation of the reconstruction of an image from a 32-channel Brain ECVT sensor using NN-MOIRT was conducted. The simulation was performed by varying the position and number of objects in the helmet-shaped Brain ECVT sensor. The alpha parameter (penalty factor) was varied from 10 to 150 with the number of iterations from 1 to 200. The RMSE (root mean square error) was calculated based on the difference between the permittivity distribution of the objects and the reconstructed image. It was found that the NN-MOIRT algorithm is more convergent and more stable for image reconstruction than the ILBP algorithm.

1. Introduction

Electrical capacitance volume tomography (ECVT) was developed based on the electrical capacitance tomography (ECT) technique to obtain a volumetric image. The volumetric effect is not obtained by stacking 2-D images but the system was designed to produce a 3-D image directly and in real time [1]. Known as volume tomography, this technique produces simultaneous information from the permittivity distribution of the area enclosed by the volumetric sensor. The ECVT system consists of three main components, namely a capacitance sensor system, a data acquisition system and a computer for image reconstruction, interpretation and display of the image.

Successful implementation of tomography depends on the selection of the appropriate sensor design in relation to the application and image reconstruction algorithm. Selection of the image reconstruction technique in accordance with the sensor model and its application is very important because it determines the quality of the resulting image. A reliable technique for the reconstruction of volumetric and dynamic objects is the neural network-multicriterion optimization image reconstruction technique (NN-MOIRT). NN-MOIRT has been used successfully for imaging two- and three-phase flow systems using ECT-shaped column with a 12-electrode sensor [2]. NN-MOIRT shows robustness to noise and its accuracy and consistency are higher compared with the iterative linear back projection (ILBP) technique and simultaneous image reconstruction technique (SIRT). For example, NN-MOIRT can distinguish small bubbles or particles in oil.
Furthermore, NN-MOIRT can be applied to linear process tomography (ultrasonic computed tomography) and non-linear process tomography (ECT) as reported in [3]; the results of the simulation and experiment showed improvement in accuracy, consistency and robustness to noise compared with the LBP and ILBP techniques. Another advantage of this technique is that it reduces the computational time and parallelism inherent in the computation. In 2007, NN-MOIRT was used experimentally to reconstruct the image of a moving object for the first time. Hereafter, volumetric imaging in real time is called ECVT [1].

In this study, NN-MOIRT was applied to reconstruct the image of a helmet-shaped Brain ECVT sensor with 32 electrodes. Brain ECVT is one of the design developments of the ECVT sensor. It is used for imaging the electrical activity of the human brain based on the permittivity distribution in the cortical area. The results of image reconstruction using NN-MOIRT were compared with those from the ILBP technique.

2. Methods

An important point in ECVT is the process of image reconstruction from the measured capacitance values between electrode pairs that is based on Poisson’s equation [4, 5]:

\[ \varepsilon(x, y) \nabla^2 \phi(x, y) + \nabla \varepsilon(x, y) \nabla \phi(x, y) = 0 \]  

(1)

where \( \varepsilon(x,y) \) is the dielectric constant distribution and \( \phi(x,y) \) is the potential distribution. The measured capacitance between pairs of electrodes can be calculated by the equation:

\[ C_i = -\frac{1}{\Delta V_i} \oint_{\Gamma} \varepsilon(x, y) \nabla \phi(x, y) \cdot \hat{n} \, dl \]  

(2)

where \( \Delta V_i \) is the voltage difference between the source and the detector electrodes of the i-th pair of electrodes. ECVT techniques generally consist of a forward problem and an inverse problem.

2.1 Forward Problem

The forward problem includes data collection of the capacitance from the electrodes that are placed around the outside of the vessel [1]. In this study, the forward problem was solved by a linearization technique using sensitivity models [4, 6]. This technique is based on the superposition theorem of electricity networks. The sensitivity model can be written as [7]:

\[ S_{ij} \equiv \frac{V_{ij} E_{sl}(x,y,z) E_{dl}(x,y,z)}{V_{si} V_{di}} \]  

(3)

where \( V_{ij} \) is the volume of the j-th voxel. \( E_{sl} \) (\( = -\nabla \phi \)) is the vector of the electric field distribution when the source electrode pair i-th is activated by voltage \( V_{si} \) and \( E_{dl} \) is the vector of the electric field distribution when the detector electrode pair is activated by voltage \( V_{di} \). Equation (3) is in linear form and can be written in matrix form as follows:

\[ C = SG \]  

(4)

where \( C \) is an \( M \)-dimension capacitance data vector, \( S \) is a sensitivity matrix, \( G \) is an \( N \)-dimension image vector, \( N \) is the number of voxels in the domain (32768 for \( 32 \times 32 \times 32 \)) and \( M \) is the number of electrode pairs \( (n \times (n - 1))/2 \) with \( n \) is the number of electrodes.

2.2 Inverse Problem

The process of image reconstruction is the inversion that involves estimating the distribution of the permittivity of the measured capacitance data. The simplest way to estimate the image vector is by using a back projection technique [4,6]:

\[ G = S^T C \]  

(5)

where \( S^T \) is the matrix transpose of \( S \).

The process of iterative image reconstruction involves a method for estimating image vector \( G \) from capacitance data vector \( C \) and minimizing the error between the measured capacitance and the estimated value, such that:

\[ SG \leq C \]  

(6)
An iterative method that is widely used to solve problems in 2-D ECT is the Landweber technique, called the linear iterative back projection (ILBP) technique. ILBP is commonly used in optimization theory [8]. This technique aims to determine the image vector by minimizing the least square error function:

\[ f(G) = \frac{1}{2} ||SG - C||^2 = \frac{1}{2} (SG - C)^T (SG - C) \] (7)

The iteration procedure, which is based on a steepest gradient descent technique, can be written as:

\[ G^{k+1} = G^k - \alpha^k \nabla f(G^k) = G^k - \alpha^k S^T (SG^k - C) \] (8)

where \(\alpha^k\) is the penalty factor of the \(k\)-th iteration, which is usually a constant. A problem of the use of the Landweber technique is that the reconstructed image depends on the number of iterations and convergence is not always guaranteed. To produce an accurate 3-D reconstructed image it takes more than one objective function. Therefore, a multi-criteria optimization technique has been developed using more than one objective function, called NN-MOIRT.

2.3 Multicriteria Optimization Image Reconstruction Technique (MOIRT)
This image reconstruction technique based on multi-criterion optimization was developed by Warsito and Fan to solve the inverse problem of 2-D ECT into 3-D ECT [2, 3]. Optimization of the image vector by simultaneously minimizing four objective functions includes [1]:

a. The negative entropy function

\[ f_1(G) = \gamma_1 \delta_1 \ln G, \quad \delta_1 = \begin{cases} 1, & \text{if } G_j > 0 \\ 0, & \text{if } G_j = 0 \end{cases} \] (9)

b. The least square error function

\[ f_2(G) = \frac{1}{2} \gamma_2 ||SG - C||^2 \] (10)

c. The smoothness and small peakedness function

\[ f_3(G) = \frac{1}{2} \gamma_3 (G^T X G + G^T \tilde{G}) \] (11)

where \(X\) is an \(N\) by \(N\) nonuniformity matrix.

d. The 3-D to 2-D matching function

\[ f_4(G) = \frac{1}{2} \gamma_4 ||H_2D G - G_{2D}||^2 \] (12)

\(H_{2D}\) is a projection matrix from 3-D onto 2-D with an \(N \times N_{2D}\) dimension. \(N_{2D}\) is the number of voxels in a layer of the volumetric image vector \(G\). \(\gamma_1, \gamma_2, \gamma_3\) and \(\gamma_4\) are normalized constants between 0 and 1. Multi-criteria optimization for image reconstruction problems is to choose an image vector that has a multi-objective function value (global objective function) \(F(G) = [f_1(G), f_2(G), f_3(G), f_4(G)]^T\) are minimized simultaneously.

2.4 Hopfield Neural Network
Hopfield neural network models (Hopfield nets) have been successfully used to solve a number of difficult optimization problems, including image reconstruction for tomography [9, 10]. To solve the problem of image reconstruction, the value of an image voxel \(G_j\) to be reconstructed is mapped to the variable output neurons \(u_j\) in Hopfield nets.

Hopfield neural network behavior is characterized by the time evolution of the state of the neuron \(u_j\) according to the following differential equation [11]:

\[ C_{0j} \frac{du_j}{dt} = - \frac{\partial E(G)}{\partial G_j} \] (13)

where \(C_{0j}\) is the capacitance of \(j\)-th neuron, and \(E(G)\) is the total energy of the Hopfield nets. The evaluation time constant is defined as:

\[ \tau = R_{0j} C_{0j} \] (14)

where \(R_{0j}\) is the resistance of \(j\)-th neuron. The energy functions for the network optimization problem is stated as [1]:

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The equation for selection of the penalty parameter is as follows:

\[ E(G) = \gamma_1 \delta_1 \log G + \frac{1}{2} \gamma_2 \| z_1 \|^2 + \frac{1}{2} \gamma_3 (G^T X G + G^T G) + \frac{1}{2} \gamma_4 \| z_2 \|^2 + \mathcal{H}(\alpha_1 z_1) + \mathcal{H}(\alpha_2 z_2) + \sum_{j=1}^{N} \int_{0}^{1} f_j^{-1}(G) dG \]  

The equation for the choice of the penalty parameter \( \alpha_k \) is as follows:

\[ \alpha_k(t) = \alpha_{0k} + \xi_k \exp(-\eta_k t) \]  

\( \alpha_{0k}, \xi_k \) and \( \eta_k \) are positive constants. The penalty parameter provides a mechanism for removing local minima by varying the direction of motion of the neurons in such a way that the ascent step is taken largely by the penalty function in the first step.

2.5 Simulation of Brain ECVT sensor

A simulation of the reconstruction of an image from a Brain ECVT sensor using NN-MOIRT was conducted by varying the position of the objects and the number of objects as shown in Figure 1. The value of relative permittivity \( (\varepsilon_r) \) of each given object was 604.55, which corresponds to the permittivity of the gray matter in the brain at a frequency of 2.5 MHz.

\[ \text{Figure 1. Variations in the number of objects in the Brain ECVT sensor.} \]

The stages of the process of image reconstruction using the neural-network approach based on multi-criteria optimization include [2]:

a. Initialization step

Set the initial state of the neuron \( u_j(0) = 0; v_j(0) = \sum(u_j(0)) \). Set steepness gain factor \( \beta = 2 \). Initialization of penalty parameter \( \alpha \) and gain parameter \( \zeta \), which affect the performance of convergence. Use \( \alpha_0 = \zeta \) for all reconstructions. Adding Gaussian noise in the simulation to test the robustness of the NN-MOIRT reconstruction technique: \( C_i = [1 + N(\mu, \sigma^2)] C \) where \( N(\mu, \sigma^2) \) is a Gaussian distribution function with mean \( \mu \) and variance \( \sigma^2 \). Set \( \mu = 0 \) and \( \sigma = 0.05 \). The initial weights are selected to be \( \omega_1(0) = \omega_2(0) = \omega_3(0) = \omega_4(0) = 1/4 \).

b. Updating step

The weights \( \omega_1, \omega_2, \omega_3 \) and \( \omega_4 \) for every iteration are updated by the following equation:

\[ \omega_i^{(n+1)} = \frac{\Delta \omega_i^{(n)} / \Delta \omega_j^{(n)}}{\sum_i \Delta \omega_i^{(n)} / \Delta \omega_j^{(n)}} \quad \Delta \omega_j^{(n)} = f_j(G(t + \Delta t)) - f_j(G(t)) \]

with \( i = 1,2,3,4 \).

c. Stopping step

The rule for stopping is determined by \( |G_j(t + \Delta t) - G_j(t)|^2 \ll 1 \) for all voxels (neurons).

In this study, reconstruction of an image with NN-MOIRT was done by iterating 200 times and variation of alpha from 10 to 150. The number of iterations and penalty factor \( \alpha \) were varied to get a stable value in the process of image reconstruction. The squared error value was calculated by the following equation [8]:

\[ \text{RMSE} = \frac{\sum |G_{\text{rec}} - G_{\text{ref}}|^2}{\sum |G_{\text{ref}}|^2} \]

\( G_{\text{rec}} \) is the reconstructed image vector and \( G_{\text{ref}} \) is the reference image vector.
3. Results

The distribution of normalized sensitivity for all 496 electrode pairs of the Brain ECVT sensor is shown in Figure 2. The sensitivity is influenced by the electric field intensity, which is spread in the domain of the ECVT sensor. The area that has many slope variations along the axial direction is an area that has a high sensitivity.

![Figure 2. Distribution of normalized sensitivity for all electrode pairs of Brain ECVT sensor.](image)

Results of image reconstruction with NN-MOIRT by varying the number of objects and object positions are shown in Figure 3.

![Figure 3. Comparison of reconstruction images in 2-D and 3-D using ILBP and NN-MOIRT.](image)
4. Discussion

The sensitivity matrix representing the sensitivity of the change in capacitance is measured on a pair of electrodes to change the value of the permittivity of the area covered by the sensor [12]. The sensitivity distribution is strongly influenced by the design of the sensors, such as sensor geometry, shape and size of the electrodes and the permittivity of the object in the sensing domain. In addition, the sensitivity distribution map is also affected by the number of voxels and sensor electrodes. The convergence of the iterative reconstruction technique is determined by the smoothness and the variation of the slope of the sensitivity distribution curve along the axial direction. The smoother the curve slope and the more variation in it, the more easily the reconstruction process will achieve convergence [1].

Based on the simulation results (Figure 3), it appears that image reconstruction using NN-MOIRT is more accurate than using ILBP technique. The object’s position in the sensing domain greatly affects the quality of the resulting image, because the sensitivity in the sensing domain varies according to Figure 2. For areas with high sensitivity the image produced tends to clear, while if the object is in a dead zone the image becomes blurred. If the object is located near the sensor, an elongation effect appears. This effect is more visible if the object is located within the sensing area with higher sensitivity rather than in the surrounding area. The parameters that affect the quality of the reconstructed image are the selection of the penalty factor and the number of iterations. In reconstruction with NN-MOIRT the smallest error was 0.4684 occurs during alpha 130 and number of iteration 116. NN-MOIRT is capable of maintaining a stable condition when the number of iterations and alpha parameter are increased.

5. Conclusions

The volumetric imaging technique NN-MOIRT was successfully applied to imaging of an object using a helmet-shaped Brain ECVT sensor with 32 electrodes. The use of multicriterion optimization produces an image that is more accurate than with other iterative reconstruction techniques, such as ILBP. NN-MOIRT is feasible for real-time volumetric imaging.

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