Electrical Impedance Sensing System Design for Abnormal Object Detection

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Abstract—This paper proposed a design for an electrical impedance (EI) sensing system. For the part of physical modeling, the harmonic electric fields of the EI sensing system are formulated by the distributed parameter element (DPE) method to calculate the electrode potentials for several injection patterns of different abnormal object distributions, and the computed electrode potentials are feed into a deep neural network (DNN) to estimate the location and size of the abnormal object. For the part of system development, an electric circuit that integrates the multiplexer and Howland pump is utilized to switch the current injection electrodes and control the injection currents. The harmonic electric fields computed by the DPE method are verified by the FEA software, and the effects of utilizing the DNN for abnormal object detection are numerically validated. The proposed design, along with a prototype of the EI sensing system, which is conducted on two kinds of materials, phantom and biological objects, have been experimentally compared.

I. INTRODUCTION

Abnormal object detection is essential and has a broad spectrum of applications. Electrical impedance tomography (EIT), which images the electrical properties within a body by using an electrode array for stimulating and measuring on the body surface [1], is a common method for abnormal object detection. In clinical medicine, the EIT has been used for monitoring regional lung ventilation in mechanically ventilated patients and for regional pulmonary function testing in patients with chronic lung disease [2]. Multi-frequency electrical impedance tomography (MF-EIT) is characterized by the collected data from subjects with brain tumors, arteriovenous malformations, or chronic stroke [3]. A three-dimensional EIT demonstrates that the impedance changes associated with evoked response paradigms can be measured non-invasively from the human head [4]. A broadband high-frequency EIT is developed for breast imaging [5], and real-time electrical impedance variations in women with and without breast cancer are discussed [6]. A portable EIT device has been developed for online thrombus detection in extracorporeal-circulation equipment [7]. Further, a cooperative-sensor technology that integrates the frequency-multiplexed EIT and synchronous multilead electrocardiogram data acquisition for noninvasive cardiovascular monitoring [8]. A coupled EIT and ultrasound system is used to spatially map the electrical properties of subsurface skin, adipose tissue, and the underlying musculature [9]. EIT can also be utilized as a human-machine interface for hand prosthesis control [10].

Modeling the electrical field is an important step in the design analysis of the EIT. The electric field belongs to a kind of scalar potential field and is formulated by partial differential equations (PDEs). For idealized shapes and boundary conditions, PDEs are commonly solved analytically. For complicated geometries, popular finite element analysis (FEA) is computationally demanding. In [11], the distributed parameter element (DPE) method is utilized for modeling a 2D or 3D physical field, which belongs to a class of scalar linear partial differential equations and investigate the effects of different electrode placement and exciting current amplitudes on the activating function distribution of the muscle nerves for the application of electrical muscle stimulation.

EIT needs to solve the non-linear, ill-posed, and ill-conditioned problem. In the early era, the Sheffield backprojection system based on the concepts from the computed tomography filter was proposed in [12], and the layer stripping method, which reconstructs the distribution of the electrical properties from the boundary toward the interior surface was proposed in [13]. However, the Sheffield backprojection and layer stripping method are considered inappropriate for many biomedical applications [1]. In recent years, the D-bar algorithm, a single-step of non-linear reconstruction method, was proposed to reconstruct a complex conductivity distribution from the 2D-EIT data [14].

Motivated by the need to develop an electrical impedance (EI) sensing system for abnormal object detection. The DPE method in [11] is utilized to design a prototype of an EI sensing system and integrated with deep neural network (DNN) for abnormal object detection. This paper provides a methodology for development of an EI sensing system. The remainder of this paper provides the following:

– The DPE method is utilized to formulate the harmonic electric fields of the objects to investigate the effects of different injection patterns on electrode potentials for different abnormal object distributions. A three-layer DNN is introduced for estimation of the location and radius of the abnormal object. The system structure of the EI sensing system and the principle of the Howland current pump to control the injection currents are introduced.

– Illustrated with two examples, the DPE method for modeling the harmonic electric field of one current injection is numerically evaluated by comparing it with FEA.
simulations, and the effects of utilizing the DNN for abnormal object detection are numerically validated. As will be demonstrated, a prototype of the EI sensing system is developed to validate the design.

II. ELECTRICAL IMPEDANCE SENSING SYSTEM DESIGN

Figure 1 illustrates the design concept of the proposed EI sensing system for abnormal object detection. As shown in Fig. 1(a), the electrode array is placed inside the phantom tank filled with normal and abnormal objects. The EI sensing system utilizes one pair of electrodes called current electrodes to inject sinusoidal currents. All electrodes are utilized as voltage electrodes for measuring the boundary electric potentials. The current/voltage electrodes are switched by the electronics system. The localization and radius of the abnormal object is estimated by the information of the boundary electric potentials by the EI sensing system. The current densities in the electric field satisfies the equation of continuity given in (1a) along with Ohm’s law, and the definition of electric potential (1b, c). In (1a), \( J \) is the current density \((A/m)\), and \( Q \) is the source current \((A/m^2)\). In (1b), \( E \) is the electric field. In (1c), \( V \) is the electric potential \((Volts)\). By substituting (1b, c) into (1a), the governing PDE (in terms of the electric potential \( V \)) is expressed in the form in (2) with two kinds of boundary conditions: 1) Dirichlet boundary condition for current density in (3a), 2) Neumann boundary condition for electric potential in (3b), \( J_b(A/m) \) and \( n \) are the inward current density and normal vector at the boundary respectively. \( V_s(Volts) \) is the electric voltage of the base.

Fig. 1(b) illustrates the method of utilizing the distributed parameter method to model the electrical field. The current is injected through the current injection electrode to the ground. The boundary condition of the current injection electrode (BC1) is current density \( J_b \). The ground (BC2) is electrical potential \( V_b \). The rest is assigned a zero Neumann \( BC_0 \) normal to the surface. The values of the voltage electrodes which equal to the electric potential averages of the elements that contact with voltage recording electrodes can be determined by dividing the sum of electrical potential for contacting elements by the number of the contacting elements.

\[
\nabla \cdot \mathbf{J} = Q; \quad \mathbf{J} = \sigma \mathbf{E}; \quad \mathbf{E} = -\nabla V \quad \text{(1a-c)}
\]

\[
\nabla \cdot (-\sigma \nabla V) = Q \quad \text{(2)}
\]

Current density: \(-n \cdot \mathbf{J} = \left\{ \begin{array}{l}
J_b \quad \text{BC}_1 \\
0 \quad \text{BC}_0
\end{array} \right. \quad \text{(3a)}
\]

Electric potential: \( V = V_b \quad \text{BC}_2 \quad \text{(3b)}
\]

The DPE method in [11] which divides the object into distributed elements and considers the geometry and boundary conditions formulates the electric field in the state-space representation:

\[
\mathbf{x} = -[\mathbf{A}_o] \mathbf{x} - [\mathbf{B}_o] \mathbf{u} \quad \text{(4)}
\]

In (4), \( \mathbf{x} \in \mathbb{R}^{N \times 1} \) = \([V_1 V_2 \cdots V_{N_e}]^\top \);

\[
\mathbf{u} \in \mathbb{R}^{N \times 1} = \left[ U_1 \cdots U_{i-1} \cdots U_{N_e, N_e} \right] ;
\]

\[
U \in \left\{ \begin{array}{l}
Q \quad \text{Element source (ES)} \\
(V_s, J_b) \quad \text{Boundary source (BS)}
\end{array} \right.
\]

\( \mathbf{x} \) is the state vector, which contains the electric potential values of \( N_e \) element. The input vector \( \mathbf{u} \) includes \( N_e \) electric potential \( Q \), \( N_d \) boundary electric potential \( V_b \), and \( N_f \) boundary current density \( J_b \). For a harmonic input \( \mathbf{u}_a e^{i \omega t} \) where \( \omega \) is the angular frequency and \( \mathbf{u} = \mathbf{u}_a \), the time derivative of the state-space variables is \( \dot{\mathbf{x}} = j \omega \mathbf{x} \). Substituting \( \mathbf{x} = \mathbf{V}_{re} + j \mathbf{V}_{im} \) and \( \mathbf{u} = \mathbf{u}_a \) into (4), the real part harmonic solution to the electric fields is obtained in (5) and imaginary part \( \mathbf{V}_{im} \) is 0.

\[
\mathbf{V}_{re} = -\left[ \sigma [\mathbf{A}_o]^{-1} + [\mathbf{A}_a] \right] [\mathbf{B}_o] \mathbf{u}_a \quad \text{(5)}
\]

For the polar coordinate, the electric field in (1c) is expressed in (6), and its norm is in (7). The values of the electric potential, radial distance, and pole angle of the element are as follows: \( v(i, j), r(i, j), \theta(i, j) \) \((i-1, j), (i, j-1)\) are the neighboring elements of the \((i, j)\) element in the tangential and radius directions in Fig. 1c.

\[
\mathbf{E} = -\frac{\partial v}{\partial r} \hat{\mathbf{e}}_r - \frac{\partial v}{\partial \theta} \hat{\mathbf{e}}_\theta \quad \text{(6)}
\]

where \( \frac{\partial v}{\partial r} = \frac{v(i, j) - v(i, j-1)}{r(i, j) - r(i, j-1)} \) \( \frac{\partial v}{\partial \theta} = \frac{v(i, j) - v(i, j-1)}{\theta(i, j) - \theta(i-1, j)} \)

\[
|\mathbf{E}| = \sqrt{\left( \frac{\partial v}{\partial r} \right)^2 + \left( \frac{\partial v}{\partial \theta} \right)^2} \quad \text{(7)}
\]

A. Inverse Method Based on Deep Neural Network

The proposed EI sensing system has an eight-electrode array. Two kinds of current injection methods are discussed in this paper: the adjacent current method and the opposite current method. Fig. 2(a) and (b) illustrate the adjacent current method and opposite current methods for detection of the abnormal and normal objects with their electrical conductivities, \( \sigma_b, \sigma_c \) \((S/m)\) respectively. \( EC_1-EC_8 \) denote the electrodes 1 to 8. Table I lists the current injection patterns of these two methods. In the EI sensing system design, all electrodes are utilized to measure the electrical potential. The adjacent current method is the current applied through adjacent electrodes in a sequence. For the first current projection, the current is injected through \( EC_1 \) (current injection electrode: \( I \)) and \( EC_2 \) (Ground: \( G \)), and all the values of electrical potential of measuring electrodes \( V_1-V_8 \) are recorded. \( EC_3 \) is the ground of the injection and measuring electrodes. For the second current injection, \( EC_5 \) is the current injection electrode, and \( EC_4 \) is the ground. To simplify the development of EI sensing system, eight injection patterns of

![Fig. 1. Design concept of an Electrical Impedance sensing system. (a) Illustration of abnormal object detection, (b) boundary conditions of the electric field, (c) adjacent element.](image-url)
Each method are utilized and listed in Table I. The sequence of projections \((I, G)\) are \((1, 2), (3, 4), (5, 6), (7, 8)\) and followed by reversing the electrode of current injection and ground \((2, 1), (4, 3), (6, 5), (8, 7)\). For the opposite current method, the current is injected through two diametrically opposed electrodes in each current projection as shown in Fig. 2(b). The sequence of projections \((I, G)\) are \((1, 5), (2, 6), (3, 7), (4, 8)\) and followed by reversing the electrodes of current injection and ground \((5, 1), (6, 2), (7, 3), (8, 4)\). Each method yields eight current projections, and each projection records eight electrical voltages. The eight-electrode EI sensing system produces \(64(=8\times8)\) voltage measurements.

The proposed EI sensing system is a circular symmetrical device. The information of each electrode is needed. A fully connected neural network of DNN is utilized to solve the non-linear inverse problem. As shown in Fig. 3, the DNN consists of one input layer connected to 64 voltage measurements, a hidden layer with three layers of \((128, 128, 64)\) neurons, and one output layer connected to three features \([x_a, y_a, r_p]\). As shown in Fig. 2(a), \(x_a, y_a\) represent the values of the centroid of the abnormal object in \(x\) and \(y\) directions, and \(r_p\) is the distance between the center of the container and the center of the abnormal object. The activation function of hidden layer is a rectified linear unit, and output layer is a maxout unit. Regression loss function uses the mean square error.

### Table I. Current Injection Patterns

<table>
<thead>
<tr>
<th></th>
<th>Adjacent Current Method</th>
<th></th>
<th>Opposite Current Method</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Seq.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td><strong>I</strong></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td><strong>G</strong></td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>8</td>
</tr>
</tbody>
</table>

As shown in Fig. 4(a), the Howland pump consists of an operational amplifier and a balanced resistor bridge. The current pass through the phantom \((I_0)\) is given by Kirchhoff’s Current Law and Ohm’s Law:

\[
I_0 = I_1 + I_2, \tag{8}
\]

where \(I_1 = \frac{V_i - V_d}{R_3}, I_2 = \frac{V_d - V_L}{R_4}\). The relationship between the output of the operational amplifier \((V_d)\) and \(V_L\) is given by the principle of non-inverting operational amplifier configuration:

\[
V_d = \left(1 + \frac{R_2}{R_1}\right) V_L. \tag{9}
\]

By substituting (9) into (8), \(I_0\) is given by (10)

\[
I_0 = \frac{1}{R_5} V_i - \frac{V_L}{R_0}, \text{ where } R_0 = \frac{R_4}{R_5 - R_4 / R_1}. \tag{10}
\]

For the special case, when the ratio of \(R_2\) to \(R_1\) is equal to the ratio of \(R_4\) to \(R_3\), \(R_0\) goes infinite. \(I_0\) is controlled by \(V_i\):

\[
I_0 = \frac{1}{R_5} V_i. \tag{11}
\]
III. NUMERICAL VERIFICATION AND ILLUSTRATIVE APPLICATION

For design analysis of the proposed EI sensing system, two sets of numerical investigations for both forward and inverse methods are performed. The first set simulates the electric field of the proposed EI sensing system by the DPE method and compares results with FEA software. The second set illustrates an example of abnormal object detection using the DNN.

A. Electric Field of Electrical Impedance Sensing System

The effectiveness of the DPE method is numerically evaluated by comparing with the COMSOL (commercial FEA software). Figure 5 shows the simulation configuration of utilizing the EI sensing system for abnormal object detection. Fig. 5(a) illustrates an example of the boundary conditions for the case that \( EC_t \) is the current injection electrode \((B_{C1}, J_0 = 1)\) and \( EC_o \) is the ground \((BC_0, V_s = 0)\). Other boundaries are set as \( BC_o \). The equations of \( BC_o \) refer to (3a, b). The mesh utilized for DPE method and FEA are shown in Fig. 5(a), (b) respectively. The number of layers in the radial and tangential directions are 14 and 80, and the total number of elements are 1120 for the DPE method. For the FEA, the number of triangular elements and degrees of freedom solved are 1981 and 4051 respectively. The parametric values in simulations are summarized in Table II, where \( I_0 \) is the current amplitude, \( f \) is the frequency, \( w_e \) and \( h_e \) are the width and height of the electrodes. As illustrated in Fig. 2(a), \( r_c \) is the radius of the container, \( r_o \) and \( \theta_o \) are the radius and polar angle of the abnormal object respectively.

![Fig. 5 Simulation configuration of the EI sensing system. (a) DPE method mesh. (b) FEA mesh.](image)

**TABLE II. PARAMETRIC VALUES OF EI SENSING SYSTEM**

<table>
<thead>
<tr>
<th>Current (mA)</th>
<th>Geometry</th>
<th>Electrical Impedance Sensing System</th>
</tr>
</thead>
<tbody>
<tr>
<td>( I_0 )</td>
<td>( r_c ), ( r_o ), ( w_e ), ( h_e ), ( \theta_o )</td>
<td>( f/(kHz) )</td>
</tr>
<tr>
<td>1</td>
<td>42, 31, 10, 8, 50</td>
<td>0</td>
</tr>
</tbody>
</table>

**Electrical conductivity (S · m⁻¹)**

<table>
<thead>
<tr>
<th>Phantom</th>
<th>( \sigma_e )</th>
<th>Biological object</th>
<th>( \sigma_e )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jelly</td>
<td>0.1406</td>
<td>Meat</td>
<td>0.4407</td>
</tr>
<tr>
<td>Acrylic</td>
<td>10⁻¹⁴</td>
<td>Fat</td>
<td>10⁻¹⁴</td>
</tr>
</tbody>
</table>

**RMS (real, imaginary) error between the DPE solutions and FEA**

\[
RMS = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (Y_{d,n} - Y_{f,n})^2}
\]

<table>
<thead>
<tr>
<th>Phantom</th>
<th>Biological object</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0024</td>
<td>0.0077</td>
</tr>
<tr>
<td>0.641</td>
<td>1.9336</td>
</tr>
</tbody>
</table>

Two examples are utilized in abnormal object detection. The first is phantom, which uses jelly and acrylic to mimic normal and abnormal objects. The second is to use real biological objects, where meat and fat represent the normal and abnormal objects. The values of parametric values of the EI sensing system are listed in Table II. The electric field distribution depends on the amplitude and frequency of the injection currents. The values of the amplitude and frequency utilized in the simulation are 1 mA and 1 kHz. The method to obtain the electrical conductivity will be discussed in section IV. Fig. 6(a, b) and Fig. 6(c, d) plot the simulated real-part electrical potentials (V) and the norm of the electric field (|E|) for the compositions of phantom and biological objects. The close agreements validate the DPE methods. The imaginary part electrical potentials are zero. The root-mean-squared-errors (RMSEs) between the DPE method and FEA solutions are quantitatively evaluated. The RMSEs are listed in Table II.

![Fig. 6. Numerical investigation of the electric field distribution. (a, b) Real part electric potential and norm of electric field for phantom. (c, d) Real part electric potential and norm of electric field for biological tissue.](image)

B. Deep Neural Network for Abnormal Object Detection

The electrical potentials of electrodes can be calculated by taking the averages of the electric potentials of the boundary elements at the electrodes using the DPE method. Then, the input vector of 64 voltage measurements with abnormal object at \((x, y)\) with radius \( r_o \) can be determined by the DPE method. An example of phantom is used to illustrate the effectiveness of utilizing the DNN structure in Fig. 3 for abnormal object detection by using the adjacent and opposite current methods.

The left column of Table III lists the range of the simulation parameters. The values of electrical conductivity are \((0.1406, 10^{-14})\) (S/m) for the normal/abnormal object in simulation. 100 and 20 data sets are used for training and testing. The tool used is the open-source Python library Keras. The RMSE of the estimated results are listed in the right column of Table III. Four scenarios are utilized for estimations. The radius of the abnormal object for Case A, B
is 14.994 mm, and Case C, D is 12.012 mm. The simulation results show that the adjacent current method has a smaller RMSE for estimation of \( y \) and \( r_m \), but a larger value for \( x \). Four simulation results are listed in Table III and demonstrated in Fig. 7. The location and size of the estimated abnormal object by both the adjacent and opposite current methods are close to the truth values.

**TABLE III. PARAMETRIC VALUES OF ABNORMAL OBJECT**

<table>
<thead>
<tr>
<th>Parameter range</th>
<th>Test results (RMSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r_m ) (mm)</td>
<td>Adjacent</td>
</tr>
<tr>
<td>0-25</td>
<td>x</td>
</tr>
<tr>
<td>12-17</td>
<td>y</td>
</tr>
<tr>
<td>( \theta_i ) (rad)</td>
<td>z</td>
</tr>
</tbody>
</table>

**Examples of estimated parameters \((x, y, r_m)\)**

<table>
<thead>
<tr>
<th>Case A</th>
<th>Case B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truth</td>
<td>Adjacent</td>
</tr>
<tr>
<td>((-8.022, -11.466, 12.012))</td>
<td>((-13.776, -2.436, 12.012))</td>
</tr>
</tbody>
</table>

**Case C**

<table>
<thead>
<tr>
<th>Case D</th>
<th>Case B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truth</td>
<td>Adjacent</td>
</tr>
</tbody>
</table>

**IV. EXPERIMENTAL RESULTS AND DISCUSSIONS**

The experimental setup to validate the DPE method and evaluate the EI sensing system is shown in Fig. 8(a). The developed electronic hardware is made by the printed circuit board (PCB), which consists of four four-channel analog multiplexers and one operational amplifier. For the Howland pump circuit shown in Fig. 4(b), the resistor values \( R_{f1}=R_{f2}=22\,k\Omega, R_{f}=R_{f1}=1\,k\Omega \) are used in the experiment. The cylinder container and electrodes are made using acrylic and copper foil. The geometry is the same as the values used in simulation (Table II). National Instrumental USB-6343 is utilized as the data acquisition system. Fig. 8(b, c) are testing objects of phantom and biological tissue used to observe the distributions of the electrical potentials of the electrodes. In Fig. 8(b), Jelly filled in the container and an acrylic cylinder are regarded as normal and abnormal tissues. In Fig. 8(c), the ground meat in filled in the container and a cylinder filled with fat are considered normal and abnormal tissues.

![Fig. 8. EI sensing system. (a) Experimental setup. (b) Phantom. (c) Biological object.](image)

**Fig. 7. Estimated results. (a)-(d): Case A to Case D.**

**Fig. 9. Electrical conductivity estimation. (a) Containers of jelly samples. (b) Experimental data.**

The calibration between the numerical methods and experimental data is needed for the experimental implementation. The simulation results show that the imaginary part electrical potentials are zero. Therefore, only the magnitude is considered in the calibration. The relationship between the magnitudes of model and experimental data is described in (13), where \( M_{DE}, M_E \) are the magnitudes of model and experiment for \( \theta^d \) data. \( M_S \) is the calibration constant, which can be determined by minimizing the sum of squared errors by (14a, b). The summation number \( (m) \) is eight since there are eight voltage measurements for one current injection.

\[
\frac{dE}{dM_S} = 0, \quad \text{where } E = \sum_{i=1}^{m} (M_{Ei} - M_S M_{D})^2
\]

\[
M_{Ei} = M_S M_{D}
\]
\[
M_j^{\text{react}} = \frac{\sum_{i=1}^{n} M_{i,j}^2 \sum_{i=1}^{n} M_{i,n}^2}{2}
\]

The functions of the electric circuit for switching current injection electrodes are tested. Fig. 10(a), (b) show the experimental results compared with the calibrated DPE method and FEA for the phantom and biological objects for the first injection pattern of the opposite current method, which \(E_C\) is the current injection electrode and \(E_C\) is the ground with \(M_5=2.25\) and \(5.23\) respectively. The results show that the simulated and experimental data have the same trend.

![Experimental results](image)

Fig. 10. Experimental results. (a) Phantom. (b) Biological object.

V. CONCLUSION

The design concept of an EI sensing system for abnormal object detection has been presented. Additional wires are connected to the electrodes to measure the voltage difference of the current injection electrode. The harmonic responses of the electric field for the object are determined by the DPE method and numerically verified by comparing results with FEA simulations. The effects of using the DNN by feeding the electrode voltage data generated from the DPE method for estimation of the location and radius of the abnormal object are numerically validated. With a prototype of the EI sensing system, the implementation and measurement of different current pattern injections have been illustrated experimentally and compared with the DPE method and FEA software. The measuring electrodes of different injection current patterns can be calibrated in future research so that this model based EI sensing system can be extended to real-time abnormal object detection.

REFERENCES


