Design Automation of a Dynamic Thorax-Like Mesh Phantom for Evaluating the Performance of Electrical Impedance Tomography System

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This work was supported in part by the National Key Research and Development Program of China under Grant 2019YFB2204500, and in part by the Science, Technology and Innovation Action Plan of Shanghai Municipality, China, under Grant 1914220370.

ABSTRACT Phantoms are used to evaluate, calibrate, and compare the performance of electrical impedance tomography (EIT) systems. This paper presents a dynamic thorax-like mesh phantom, which mimics the changes in electrical conductivity distribution within a human thorax at different time frames. Furthermore, element merging and contour smoothing, electrode placement techniques, and PCB design automation methods are proposed to simplify, optimize the mesh phantom, and reduce the hardware implementation cost. To verify the accuracy of the mesh phantom and its PCB, SPICE simulations and experimental testings are performed to obtain the conductance of the mesh phantom and reconstruct the images through the EIDORS software. These images achieve an image correlation coefficient (ICC) of 0.680 (model versus SPICE simulation) and 0.9098 (SPICE simulation versus measurement result), respectively. This demonstrates the validity of our proposed dynamic thorax-like mesh phantom.

INDEX TERMS Electrical impedance tomography (EIT), thorax-like mesh phantom, simulation program with integrated circuit emphasis (SPICE), printed circuit board (PCB), image correlation coefficient (ICC).

I. INTRODUCTION

Electrical Impedance Tomography (EIT) is a clinical imaging system, which provides supplementary modality to computed tomography (CT) and magnetic resonance imaging (MRI) techniques as it is non-invasive, non-thermal, and radiation-free [1], [2]. Assessing the performance of EIT systems [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17] is a very challenging task in vivo environment. As shown in Figure 1, improving the phantom design is essential for evaluating and calibrating the EIT system in vitro environment [18], [19].

The phantoms are generally classified into (i) physical phantoms [14], [20], [21], [22], [23], [24], [25], [26], [27], [28], and (ii) mesh phantoms [16], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38]. (i) Physical phantoms are implemented using a container filled with a conductive medium, usually saline water [14], [22], [23], [25], [26], [28]. Conductive copper and insulative nylon objects, which resemble the human heart and lungs, are inserted into the container to simulate perturbations in the conductive medium. This type of phantom is very hard to reproduce the same measurement result due to the fluctuation in conductivity, such as the exact placement of objects, evaporation of saline water, and its concentration [20], [21], [24], [27]. (ii) Mesh phantom consists of a network of resistors soldered onto the printed circuit board (PCB), where the topology of interconnection creates the corresponding shape, size, and conductivity distribution [29], [30], [36], [37]. Thus, the mesh phantom allows a more predictable, stable, and reproducible method to evaluate the performance of EIT systems.
To date, there are six different designs of mesh phantoms: the Cardiff phantom [30], the wheel phantom [31], the first Göttingen phantom [33], the second Göttingen phantom [34], the FEM phantom [35], and the thorax-like mesh phantom [38]. Unlike our prior work [38], the conductivity distributions of these mesh phantoms [30], [31], [33], [34], [35] are either in a circular or octagon shape, which does not mimic the real human thorax. Furthermore, none of these works are able to mimic the dynamic changes within the human thorax [39], [40]. Thus, this motivates us to further explore the opportunity to develop a realistic dynamic mesh phantom, where the distribution of human-like conductivity changes in different states.

The contributions of our work are summarized (Figure 2) as follows:

1) **Optimizations of Mesh Phantom**: For the ease of soldering and cost of hardware implementation, it is important to optimize the number of resistors on a given size of PCB board without compromising the image’s quality. Therefore, we propose elements merging and contour smoothing techniques to reduce the number of resistors. As a result, the number of resistors and resistor density has reduced from 4,616 to 313 and from 33 to 3 per cm$^2$. We also optimize the electrode placement to improve the reconstructed image quality. The reconstructed images of mesh phantom with dynamic parts in different regions only show a slight degradation in the image compared to the ideal model.

2) **Dynamic Mesh Phantom**: To mimic the changes in electrical conductivity distribution within a human thorax, we propose discretization component selection and dynamic component switching (DCS) techniques to create a dynamic change in an arbitrary region of the phantom while achieving a highly recognisable reconstructed image at different time frames.

3) **PCB Design Automation of Mesh Phantom**: To further reduce the complexity of PCB fabrication, an automated PCB design flow is developed to implement the mesh phantom using MATLAB programming language. The measurement result of PCB prototype achieves an image correlation coefficient (ICC) of 0.9098 compared to the SPICE simulation result.

The rest of this paper is organized as follows. Section II provides a background understanding of developing a mesh phantom and using SPICE simulation and EIDORS program to reconstruct the image. Section III provides the details of our proposed dynamic thorax-like mesh phantom design method with PCB automation. Section IV presents the experimental results and discusses the effectiveness of each proposed technique. Finally, the conclusion is drawn in Section V.

II. PRELIMINARIES

A. MESH PHANTOM

A basic mesh phantom is created by translating the finite element method (FEM) modeling into a solvable matrix, which represents the electrical connectivity of the mesh [35]. The FEM modeling computes and decomposes any arbitrary shape (Figure 3(b)) into triangle elements (Figure 3(a)).

The coordinates of a triangular element $(x_1, y_1), (x_2, y_2)$, and $(x_3, y_3)$, the admittance between each node are derived as follows [35]:

$$G_{12} = \frac{\sigma_e}{2\Delta} \left[ (y_2 - y_3)(y_3 - y_1) + (x_3 - x_2)(x_1 - x_3) \right],$$

(1)
in Section III.

allows us to optimize the number of resistors, interconnect
tivity. The blue area indicates the conductivity value of the
the same, and different colors represent different conduc-
reconstructed image is composed of multiple triangle ele-
struct the images of a thorax-like mesh phantom based on
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\frac{\sigma_e}{\Delta}[(y_2 - y_3)(y_1 - y_2) + (x_3 - x_2)(x_2 - x_1)], (2)
\frac{\sigma_e}{\Delta}[(y_3 - y_1)(y_1 - y_2) + (x_1 - x_3)(x_3 - x_1)], (3)
where \Delta = x_1y_2 - x_1y_3 - x_2y_1 + x_2y_3 + x_3y_1 - x_3y_2, and \sigma_e
is the conductivity inside the triangle elements.

B. SIMULATION VERIFICATION OF MESH PHANTOM
To ensure the proper functionality and accuracy of the mesh
phantom before fabricating the design onto the printed
circuit board (PCB), its circuit netlist is verified through
a Simulation Program with Integrated Circuit Emphasis
(SPICE) circuit simulator. A differential current is injected
through a pair of terminals and measures the potential differ-
ences across the remaining pairs of terminals. These actions
are repeated for all N terminals through successive rota-
tions to obtain an N×N-3 matrix for creating one frame
of the image. As compared to other reconstruction algo-
rithms [42], [43], [44], [45], [46], [47], [48], [49], [50],
[51], we have chosen the Electrical Impedance Tomography
and Diffuse Optical Tomography Reconstruction Software
(EIDORS) [41] software as it can be directly used to recon-
struct the images of a thorax-like mesh phantom based on
the potential difference matrix. As shown in Figure 3, the
reconstructed image is composed of multiple triangle
elements. The conductivity within a triangle element remains
the same, and different colors represent different conduc-
tivity. The blue area indicates the conductivity value of
the region is smaller than the average. The verification method
allows us to optimize the number of resistors, interconnect
topology, and electrode placement, which will be discussed
in Section III.

C. EVALUATION OF IMAGE QUALITY
To evaluate the quality of reconstructed EIT images, we
have adopted the image correlation coefficient (ICC) anal-
ysis method to understand the similarity between two
images [52], [53], [54]. The formula of ICC is as follows:

\[ ICC = \frac{\sum_{i=1}^{n} (y^*_i - \bar{Y}^*) (y'_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (y_i - \bar{Y})^2 \sum_{i=1}^{n} (y'_i - \bar{Y})^2}} \]

where \( Y' = [y'_1, y'_2, \ldots, y'_l] \) and \( Y^* = [y^*_1, y^*_2, \ldots, y^*_l] \)
are the expected and the real outputs of the conduc-
tivity value, respectively. A larger ICC value indicates
better imaging quality and modeling accuracy of the mesh
phantom.

III. PROPOSED DYNAMIC MESH PHANTOM METHOD
In this work, the design methodology of the basic mesh
phantom has been further extended to a thorax-like mesh
phantom. Our work is based on the human model provided
by Netgen’s shape library [55]. The contours of a human’s
thorax and lungs are extracted from computed tomography
(CT) of the healthy human being. However, this library does
not clearly present the contours of a heart, so we have simply
used a round shape as a substitute for FEM modeling. The
conductance value of the lungs and heart is defined as 0.392
and 0.637, respectively [56]. For the conductance value for
the remaining parts of the human model, we took an average
value of different types of tissues and defined it as 0.5.

To mimic the changes in electrical conductivity distribution
within a human thorax, we propose a dynamic thorax-like
mesh phantom with the optimization of resistor number and
electrode placement to further reduce the complexity of PCB
fabrication, and an automated PCB design flow to implement
this phantom.

A. OPTIMIZATION METHODS
Method 1 - Resistors Reduction Technique: As shown
in Figure 3(b), the original thorax-like mesh provided by
the Netgen shape library has a total of 4,626 edges in the FEM
model. Each edge represents a resistor component. To fab-
ricate the mesh design onto an A4 paper size PCB board
(21cm×29.7cm), similar to the size of our body thorax,
it is important to optimize the number of resistors on a
given size of PCB board without compromising the image’s
quality. This will also simplify the soldering problem and
reduce the cost of hardware implementation. For the con-
venience of soldering and to make use of surface mount
technology (SMT), we have restricted the number of resis-
tors per cm² to no more than 3. Therefore, we propose
a method to reduce the number of resistors, which con-
ists of two steps: (i) elements merging and (ii) contour
smoothing.

(i) Elements Merging Technique: refers to the merging
of triangle elements into larger triangle elements by averaging
the adjacent nodes into one node. The detail of elements
merging is presented in Algorithm 1. The algorithm traverses
all nodes on the contour (Line 5). If there are any M adjacent
nodes where the angle between the M points is greater than
D, these nodes are merged into one node (Line 6-9). For
the nodes that are not on the contour, the algorithm merges
Algorithm 1 Merging Algorithm

Input: Location of all nodes \( n \) in the original FEM;
Output: FEM model with smaller nodes;

1: Set \( N_m \) as the collection of output FEM’s nodes;
2: Set \( C_t, C_l, C_h \) as the collection of points on the contour of the chest, lungs and heart, respectively;
3: Set \( E \) as the collection of elements;
4: Set \( \angle N \) as the angle between \( n_{i-1} \) and \( n_{i+1} \);
5: for each node \( n \in C_t, C_l, C_h \) do
6: if \( \angle N > 170^\circ \) then
7: Add \( n_i = (n_i + n_{i-1} + n_{i+1})/3 \) to \( N_m \)
8: delete \( n_{i+1} \) from \( C_t, C_l, C_h \)
9: end if
10: Add \( n_i \) to \( N_m \)
11: end for
12: for \( i = 1 \) to 3 do
13: Initialize a set \( T \);
14: for each element in \( E \) do
15: Set \( n_1, n_2, n_3 \) as the three vertices of the element
16: Add \((n_1 + n_2 + n_3)/3\) to \( T \)
17: end for
18: \( E \leftarrow T \)’s corresponding set of elements
19: end for
20: Add \( E \)’s nodes to \( N_m \);

Each triangle element’s \( M \) nodes into one node (Line 14-17) and iterates \( T \) times (Line 12). Based on our preliminary experiments to achieve a good trade-off between the quality of reconstructed image quality and the number of resistor components, \( M \) and \( T \) have been determined to be 3 and degree to be 170°. Figure 3(c) presents the reduced version of thorax-like mesh phantom using the “elements merging” technique.

(ii) Contour Smoothing Technique: removes the sharp contour of the lungs’ shape by reducing the number of clustered nodes within a defined distance. As shown in Figure 3(c), the sharp contours with corners that are less than 90° are circled in red. As shown in Figure 3(d), the number of resistors near these corners has been reduced using the element merging technique to fit the resistors in the PCB.

Method 2 - Electrodes Optimization Technique: The number of electrodes and their placement affects the quality of the reconstructed EIT image [57], [58], [59], [60]. Due to the irregular shape of the human’s thorax, it is impossible to evenly place all electrodes on the mesh phantom, unlike the circular phantom. Thus, we explore different types of electrode placement based on symmetry (mound or flat or asymmetrical), skew (right or left), spread (narrow spread or wide spread), and the number of peaks (unimodal, bimodal, or multiple peaks) and compare the quality of the reconstructed image, hoping to identify an optimal electrode placement without compromising the image quality. The result of different placements is discussed in Section IV-B.

![FIGURE 4. Procedure of applying DCS techniques to a mesh phantom with 313 resistors: (a) Select the region for dynamic changes, (b) Identify components for discretization, (c) first state change in DCS, (d) second state change in DCS.]

B. DYNAMIC THORAX-LIKE MESH PHANTOM USING DCS TECHNIQUES

To create a perturbation in the resistive network (mesh phantom) (Figure 4(a)) without causing errors in the image reconstruction at different time frames [58], [59], we have to identify the number of resistors at the correct locations for discretization (Figure 4(b)), which replaces the resistor with the equivalent resistance of two resistors connected in series \( (R_X = R_1 + R_2) \) (Figure 5(a)). In particular, the discretization ratio (DR) refers to the ratio between the discretized resistor and the original one as follows:

\[
DR = \frac{R_1}{R_X}.
\] (5)

It is important to identify this ratio to ensure good image quality, which will be discussed in Section IV. This technique is termed Discretization Component Selection (DCS-I). As illustrated in Figure 4(c), controllable voltage-control relays (switches) are used to short one of the two resistors to create a change in the resistance path. These switches are turned either “ON” or “OFF” using a microcontroller at different time frames to create gradual changes in the resistive network (Figure 4(d)). These resistors and switches are soldered
FIGURE 5. (a) The Discretization Component Selection (DCS) of resistor RX into R1 and R2 (b) The PCB layout of plug board.

FIGURE 6. Our proposed method of constructing the outline of mesh phantom. (a) Linear transformation, (b) RC circuit network near the electrodes, (c) Solder pads on each node of the resistive network.

onto a separate PCB plug board (Figure 5(b)), which can be connected to the original location. This technique is termed Dynamic Component Switching (DCS-II).

C. DESIGN AUTOMATION OF THE MESH PHANTOM ON PRINTED CIRCUIT BOARD (PCB)

The implementation of the mesh phantoms [16], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38] requires a meticulous handcrafting design of the PCB layout. Thus, we propose the following PCB design automation for the mesh phantom: (i) contour construction of the mesh phantom, (ii) placement and routing of resistors, and (iii) implementation of dynamic mesh phantom. We use the MATLAB programming language to create the entire design automation flow and generate the PCB file according to the Protel PCB 2.8 ASCII format.

Contour Construction of the Mesh Phantom: A coordinate transformation is applied to each node of the mesh phantom to allow its contour to be uniformly distributed over the PCB board (Figure 6(a)). Solder pads are automatically added to each node in the resistive network for the ease of measuring the resistance during the testing phase (Figure 6(c)).

Placement and Routing of Resistance Components: Resistors are placed in between the nodes with wires connecting to them and the values of these resistors are rounded off to the nearest available resistance values (Figure 7(a)).

Implementation of Dynamic Mesh Phantom: Based on the DCS techniques, the selective resistors are replaced with 100-mil PCB connector headers so that the plug boards can be inserted to mimic the gradual changes in the mesh phantom (Figure 7(b)).

PCB components: Beside generating the PCB file for fabrication on FR4 substrate, we have used the following discrete components for the PCB fabrication of the proposed mesh phantom as presented in Table 1.

IV. RESULTS AND DISCUSSION

As discussed in Section II-C, the image correlation coefficients (ICC) are used to evaluate the imaging quality of mesh phantoms for each optimization step.
A. EVALUATION OF THE RESISTOR REDUCTION OPTIMIZATION TECHNIQUE

The original thorax-like mesh phantom based on the Netgen shape library [41] has a total number of 4,626 edges (resistors). As shown in Figure 2(a), the maximum resistor density (number of resistors on the PCB board per cm²) has reached up to 33 components per cm², which is not practical to fabricate the PCB due to the physical size of the surface mounted technology (SMT) resistors. Note that the size of common surface mount technology (SMT) 0603, 0805 and 1206 resistors are 1.6mm × 0.8mm, 2mm × 1.25mm, and 3.2mm × 1.6mm, respectively. SMTs with a footprint smaller than 0603 may not be suited since they have a smaller voltage break tolerance and a larger resistance tolerance of up to 10%.

As presented in Table 2, the use of merging and smoothing optimization techniques without compromising the ICC has reduced the number of resistors by 699 (6.91 × reduction) and 313 (14.78 × reduction), respectively. Similarly, the maximum resistor densities have reduced down to 11 and 3 components per cm², respectively. The final area of the thorax-like mesh is 483.7cm², which fits well onto the A4 size PCB with a dimension of 21cm × 29.7cm.

B. EVALUATION OF ELECTRODE PLACEMENT

To determine the optimal placement of electrodes through SPICE simulation and evaluate the image quality with ICC, we have explored different types of electrode’s placement based on symmetry (mound or flat) or asymmetrical, skew (up or bottom or right or left), spread (narrow spread or wide spread), and number of peak (unimodal, bimodal or multiple peaks). Thus, we have concluded to use 4 general electrode placement methods to understand the optimal placement of electrodes. We did not explore number of peaks as it is not easy to use in practical situation in EIT system.

Figure 8 shows the four types of electrodes’ placement and their corresponding reconstructed images: (i) mesh-A uses asymmetrical and skew left electrodes’ placement strategy, (ii) mesh-B and mesh-C use asymmetrical and skew bottom and up electrodes’ placement strategy, and (iv) mesh-D uses evenly spread placement strategy. The reconstructed images are divided into four regions to obtain the mean and variance of the ICC, and the results are presented in Table 3. It is observed that the density of electrodes affects the corresponding regional ICC. To obtain satisfying EIT imaging quality, the variation of ICC among the regions needs to be minimized and it must be at least 0.5 [52]. Thus, mesh-D is chosen as it achieves the highest ICC with acceptable regional variation (Figure 8(d)).

C. EVALUATION OF DYNAMIC MESH PHANTOM

Selection of Discretization Ratio (DR): To create a perturbation in the resistive network within the mesh phantom (Figure 4(a)) without causing errors in the image reconstruction at different time frames [58], [59], we need to identify the suitable discretization ratio (DR) for the DCS techniques. The SPICE simulations are used to verify 100 different mesh phantom and identify the suitable DR value. As shown in Figure 10, when the DR decreases, the perturbation becomes more apparent in the reconstructed image along with the increase in ICC. The EIT image with a DR of 0.1 achieves the best ICC of 0.631, where the ICC value for the original mesh is 0.691.

Selection of Discretization Location: Upon determining the DR of 0.1, we applied DCS techniques to different parts of the lung region. Figure 11 illustrates 3 distinct discretization locations in the top, middle, and bottom of the right lung, respectively. The ICC of these reconstructed images is 0.642, 0.631, and 0.680, respectively. Clearly, our DCS technique is applicable to different parts of the lung area without compromising the image’s quality. We have selected the ‘middle’ discretization location to clearly observe the perturbation of the dynamic mesh phantom.

D. PCB FABRICATION AND TESTING VALIDATION

Figure 9 illustrates the fabricated PCB board using FR4 material and the outline of the board resembles the human thorax-like shape, which is 255.4 × 196.6 mm². Resistors with 1% tolerance and a temperature coefficient of ±200ppm/°C are assembled onto the PCB. Each plug board is fabricated on a 28.4 × 10.5 mm² rectangular board. To validate the accuracy of the fabricated PCB, we have tested it with our 16-electrode EIT system [11] and reconstructed the image using the measured result, and compared it with the SPICE simulation. Figure 12 presents the reconstructed image with an ICC of 0.9098.
TABLE 3. The statistics study of four different implementation of dynamic mesh phantoms.

|      | I    | II   | III  | IV   | Left (I-III) | Right (II-IV) | Top (I-II) | Bottom (III-IV) | Mean  | Variance* |
|------|------|------|------|------|-------------|--------------|-----------|----------------|-------|-----------|
| mesh-A | 0.599 | 0.433 | 0.803 | 0.074 | 0.791       | 0.254        | 0.516     | 0.439          | 0.477 | 0.095     |
| mesh-B | 0.552 | 0.461 | 0.839 | 0.722 | 0.695       | 0.591        | 0.506     | 0.781          | 0.643 | 0.029     |
| mesh-C | 0.545 | 0.553 | 0.761 | 0.659 | 0.653       | 0.606        | 0.549     | 0.710          | 0.629 | 0.010     |
| mesh-D | 0.644 | 0.533 | 0.828 | 0.716 | **0.736**   | **0.624**    | **0.588** | **0.772**      | **0.680** | **0.015**  |

*: The variance of the four regional ICCs

FIGURE 9. The top view of dynamic mesh phantom with the plug boards onto the PCB.

FIGURE 10. SPICE Simulation results using different discretization ratio (DR) to obtain the ICC values. The DR of each line is: (a) 0.7, (b) 0.5, (c) 0.3, (d) 0.1, (e) 0.05.

V. CONCLUSION

A dynamic thorax-like mesh phantom is designed and fabricated on an A4 PCB board to evaluate the performance of EIT systems. This phantom mimics the changes in electrical conductivity distribution within a human thorax at 4 different time frames while achieving an average ICC of 0.651. Several optimization techniques have reduced the number of resistors and resistor density from 4,616 to 313 and from 33 to 3 per cm². To verify the accuracy of the mesh phantom, SPICE simulation and experimental testing are performed on the fabricated PCB to obtain the conductance of the mesh phantom and reconstruct the images through the EIDORS software. These images achieve an image correlation coefficient (ICC) of 0.680 (model and SPICE simulation) and 0.9098 (SPICE simulation and measurement result), respectively.

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