Research Article

Width Optimization of Array Electrode for Human Lung Electrical Resistance Tomography System Based on prior Knowledge

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In electrical resistance tomography (ERT) technology for human lung, under the same experimental conditions, the width of the sensitive field boundary electrode has a significant impact on the calculation accuracy of the inverse problem besides the finite element model (FEM) topology. Aiming to improve the quality of reconstructed images, the FEM for human lung was set up based on prior knowledge. On this basis, the electrode width of the FEM was optimised by comparing the morbidity degrees of the sensitivity matrix and Hessian matrix, the uniformity of sensitivity distribution, and the quality of reconstructed images, which can improve the accuracy of solving the inverse problem significantly.

1. Introduction

In recent years, critical respiratory diseases have become a hot area of critical care medicine and one of the primary directions of disease prevention and control in China with features of high complexity, morbidity, mortality, and risk of great harm. Respiratory diseases have become one of the diseases that seriously threaten the health of Chinese residents, according to the statistical results of Vols. 2013–2017 of China Health and Family Planning Statistical Yearbook and Vols. 2018 and 2019 of China Health Statistics Yearbook [1–7]. Increasing population ageing, national smog and haze, influenza pneumonia, highly pathogenic avian influenza, and other factors will increase the morbidity and mortality of critical respiratory diseases in China, which has caused widespread attention. Compared with the epidemiological results of foreign countries, the status quo of the treatment of critical respiratory diseases in China is not optimistic. The mortality rate of critical respiratory diseases in China is much higher than that in Western developed countries. Therefore, the prevention and treatment of critical respiratory diseases are acute.

Due to the complexity of critical respiratory diseases, the current clinical treatment plan depends on the individual patient. Therefore, timely assessing the effectiveness of medical

measures and accurately grasping the changes in the progress of lung diseases is an essential basis for successful treatment of critical respiratory diseases. However, currently, there is a lack of clinically effective means for real-time monitoring and quantitative evaluation of critical respiratory diseases.

Electrical tomography (ET) technology consists of 4 different branches, namely, electrical impedance tomography (EIT) [8–14], ERT [15–20], electrical capacitance tomography (ECT) [21–27], and electromagnetic tomography (EMT) [28–33], among which the ERT technology is a new generation of medical imaging technology and a simplified form of the EIT technology when only the change of conductivity/resistivity of the sensitive field is considered, having three outstanding advantages of functional imaging, no damage, and medical image monitoring. Compared with other monitoring methods, ERT technology has incomparable advantages in real-time monitoring and quantitative evaluation of critical respiratory diseases.

2. Basic Principles of Human Lung ERT

Human lung ERT technology is based on the characteristics that different human tissues and organs have different conductivities/resistivities. Various physiological and pathological conditions often correspond to conductivity/resistivity changes of

certain tissues and organs. Firstly, a safe excitation current signal is applied on the electrode array on the body surface to establish a sensitive field in the lungs. Secondly, the effective boundary voltage of the sensitive field is obtained through the data acquisition circuit. Finally, according to the effective boundary voltage of the sensitive field, the image reconstruction algorithm is employed to solve the inverse problem of the human lung ERT to obtain the conductivity/resistivity image distribution of tissues and organs (including lungs, heart, and spine) in the sensitive field.

The current density $\mathbf{J}$, electrical conductivity distribution σ , electrical potential distribution Φ , and electric field strength $\mathbf{E}$ in the sensitive field region Ω of the human lung ERT satisfy Equations (1)–(3). By simplifying these equations, the mathematical model of the sensitive field of the human lung ERT can be obtained, as shown in Equation (4):

$$\nabla \cdot \mathbf{J} = 0, \quad (1)$$

$$\mathbf{J} = \sigma \cdot \mathbf{E}, \quad (2)$$

$$\mathbf{E} = -\nabla \Phi, \quad (3)$$

$$\nabla \cdot (\sigma \nabla \Phi) = 0. \quad (4)$$

The calculation of forward problem for human lung ERT is to calculate the potential distribution of the sensitive field generated by the given boundary stimulating electrical signal to obtain the effective boundary voltage value for solving the inverse problem, based on the known or given conductivity/resistivity distributions of tissues and organs (including the lungs, heart, and spine) within the sensitive field region. Due to the irregular geometry of the measured field, it is a challenge to use analytical methods to obtain analytical solutions to the positive problem through theoretical derivation. The numerical calculation method of FEM, which is more adaptable to the geometric shape of the measured field, is usually used to calculate the forward problem.

In the FEM-based calculation process of the forward problem of the human lung ERT, the current density $\mathbf{J}$, electrical conductivity distribution σ , electrical potential distribution Φ , and total coefficient matrix $\mathbf{K}$ in the region Ω of the sensitive field satisfy the following relationship, as shown in equations (5)–(8):

$$F(\Phi) = \frac{1}{2} \int_{\Omega} \nabla \cdot (\sigma \nabla \Phi) d\Omega - \oint_S \mathbf{J} \Phi dS = \min, \quad (5)$$

where S is the boundary of the region Ω of the sensitive field:

$$F(\Phi) = \frac{1}{2} \Phi^T \mathbf{K} \Phi - \Phi^T \mathbf{J}, \quad (6)$$

$$\mathbf{K} = \sum_e \tilde{\mathbf{K}}_e, \quad (7)$$

$$[\mathbf{K}][\Phi] = [\mathbf{J}]. \quad (8)$$

The so-called image reconstruction is to solve the conductivity/resistance image distribution of tissues and organs in

the sensitive field based on the given boundary excitation electrical signal and the corresponding effective boundary voltage, which is essential to the human lung ERT. In the two types of different image reconstruction methods for the human lung ERT, although dynamic imaging can achieve real-time imaging, static imaging has a wider application range and higher clinical value because the latter can present the absolute value of the conductivity of tissues and organs. People can diagnose different tissues and organs (including lungs, heart, and spine) as normal tissues or diseased ones according to their conductivity/resistivity values.

3. Comparison of Different Electrode Widths of Sensitive Fields

When the boundary curve equation of lungs is determined, the width of the sensitive field boundary electrode only depends on the electrode angle. Although the optimisation of electrode width of the ERT system is realized in [34], only four different electrode widths were compared, and there were some irrationalities in comparing the calculation accuracy of forward problem and selecting the image reconstruction results of Newton–Raphson algorithm. In the process of image reconstruction for the Newton–Raphson algorithm, the sensitivity matrix can be fixed, so it is meaningful to compare the sensitivity matrix. However, the accuracy of forward problem cannot be evaluated by only one set of distribution, and the optimal image reconstruction result cannot be determined in advance according to the image correlation coefficient, but only according to the algorithm error.

Now, the FEM for ERT is chosen and shown in Figure 1, which contains 537 nodes and 880 finite elements and the number of electrodes is 16. The data acquisition adopts the adjacent incentive mode, which is widely used in ERT. The excitation current is 1 mA. The number of elements used in the FEM has a certain influence on the simulation accuracy, and the number is determined by comparing the root mean square values, the time of calculating the effective boundary voltage values, and the time of calculating the sensitivity matrix. The FEM not only improves the degree of region fitting but also improves the ill-conditioned degree of the sensitivity matrix [34]. Based on prior knowledge, the internal tissue and organ distribution of the FEM for human lung ERT is set up, as shown in Figure 2. On this basis, the morbidity degrees of sensitivity matrix and Hessian matrix, the uniformity of sensitivity distribution, and the quality of reconstructed images at electrode angles of 1.8750 degrees, 3.7500 degrees, 5.6250 degrees, 7.5000 degrees, 9.3750 degrees, 11.2500 degrees, and 13.1250 degrees are compared and analysed.

3.1. Comparison of Ill-Conditioned Degrees of Sensitivity Matrix and Hessian Matrix. The internal tissue and organ distribution in the FEM for human lung ERT is shown in Figure 2, and the condition numbers of the sensitivity matrix are 5.3077×10^6 , 5.2601×10^6 , 5.0142×10^6 , 4.8788×10^6 , 4.5361×10^6 , 4.3041×10^6 , and 3.8943×10^6 at electrode

FIGURE 1: Schematic diagram of the FEM for ERT.

angles of 1.8750 degrees, 3.7500 degrees, 5.6250 degrees, 7.5000 degrees, 9.3750 degrees, 11.2500 degrees, and 13.1250 degrees, respectively. When the regularization factor is 10^{-5} , the condition numbers of Hessian matrix are 1.8154×10^2 , 1.7930×10^2 , 1.8055×10^2 , 1.7888×10^2 , 1.7993×10^2 , 1.7838×10^2 , and 1.7928×10^2 at electrode angles of 1.8750 degrees, 3.7500 degrees, 5.6250 degrees, 7.5000 degrees, 9.3750 degrees, 11.2500 degrees, and 13.1250 degrees, respectively.

3.2. Comparison of Uniformity of Sensitivity Distribution. The electrodes are evenly distributed and numbered anticlockwise. The electrode pair N-M means that the electrodes N and M are used as excitation electrodes or measurement electrodes. When the electrode pair 1-2 is the excitation electrode, parts of the sensitivity distribution corresponding to the FEM are shown in Figure 3, and the maximum values, the minimum values of the corresponding sensitivity matrices, and the calculated P values by using Equation (9) are shown in Table 1, which are used to evaluate the uniformity of sensitivity distribution. It is usually believed that the accuracy of inverse problem can be improved by improving the uniformity of sensitivity distribution.

$$P = \frac{\sum_{i=1}^M \sum_{j=2}^M |p_{ij}|}{M}, \quad (9)$$

where p_{ij} is given by

$$p_{ij} = \frac{S_{ij}^{\text{dev}}}{S_{ij}^{\text{avg}}}, \quad (10)$$

where S_{ij} is the sensitivity of the electrode pair of $i-j$ and S_{ij}^{avg} and S_{ij}^{dev} are the mean and standard deviation of the sensitivity matrix with the triangular finite element area coefficient.

It can be seen from Table 1 and Figure 3 that the sensitivity distribution is the most uniform when the electrode angle is 13.1250 degrees.

3.3. Comparison of Image Reconstruction Quality. Based on prior knowledge, 6 distributions of internal tissues and organs in the FEM for human lung ERT are shown in Figure 4. The dark red area is the pathological lung tissue. The finite element model shown in Figure 1 is refined and

used to calculate the forward problem and obtain the boundary voltage measurement values. The image reconstruction algorithm draws on the modified Newton-Raphson algorithm proposed in [35], and the specific process is as follows:

Step 1: set the algorithm parameters, including the maximum iteration number and the regularization factor, which have an important influence on the results of image reconstruction.

Step 2: calculate the sensitivity matrix $f'(\rho^{(0)})$ corresponding to the internal tissue and organ distribution of the FEM for human lung ERT in Figure 2.

Step 3: randomly generate the diagonal matrix $\mathbf{M}_{\text{num} \times \text{num}}^{(k)}$, the initial seed group with the particle number of $\text{num}_{\text{particle}}$, and the initial velocity vector $\mathbf{V}$ of the particles and optimise the main diagonal elements of the diagonal matrix $\mathbf{M}_{\text{num} \times \text{num}}^{(k)}$ by using the balance method based on the improved particle group algorithm. The fitness function selected is presented as

$$F(\mathbf{M}_{\text{num} \times \text{num}}^{(k)}) = \frac{P}{\text{cond}(\mathbf{Y})}, \quad (11)$$

where cond is the condition number, the expression of $\mathbf{Y}$ is as shown in Equation (12), and P is a penalty function, the expression is as shown in Equation (13):

$$\mathbf{Y} = \mathbf{M}_{\text{num} \times \text{num}}^{(k)} \cdot \left\{ [f'(\rho^{(0)})]^T f'(\rho^{(0)}) + \mu^{(k)} E \right\}^{-1} \cdot [f'(\rho^{(0)})]^T, \quad (12)$$

$$P = \begin{cases} 1 & \text{cond}(\mathbf{M}_{\text{num} \times \text{num}}^{(k)}) \leq \text{cond}(\mathbf{Y}), \\ 10^{-10} & \text{cond}(\mathbf{M}_{\text{num} \times \text{num}}^{(k)}) > \text{cond}(\mathbf{Y}). \end{cases} \quad (13)$$

Step 4: Take the reconstruction result of the linear backprojection algorithm as the initial estimated value $\rho^{(1)}$ of the resistivity distribution, calculate the forward problem to obtain the calculated value $v^{(1)}$ of the boundary voltage of the sensitive field, and substitute it into Equation (14) to get $E^{(1)}$, and substitute $\rho^{(1)}$ and $E^{(1)}$ into the optimal value $\mathbf{b}_{\text{estr}}$ and the minimum error value b_{estf} of the resistivity distribution of the sensitive field:

FIGURE 2: Schematic diagram of the internal tissue and organ distribution based on prior knowledge.

$$E^{(k)} = \frac{1}{2} \left(\|v^{(k)} - v_0\|_2 \right)^2, \quad (14)$$

where v_0 is the measured value of the boundary voltage of the sensitive field.

Step 5: the termination of the algorithm is based on the criteria of the number of iterations and the allowable error of the algorithm. If it is satisfied, the algorithm returns the optimal value $\mathbf{b}_{\text{estr}}$ and the minimum error value b_{estf} of the resistivity distribution of the sensitive field; otherwise, go to Step 6.

Step 6: calculate $\Delta\rho^{(k+1)}$ according to equations (15) and (16):

$$\Delta\rho_1^{(k+1)} = -Y(f(\rho^{(k)}) - \mathbf{v}_0). \quad (15)$$

$$\Delta\rho^{(k+1)} = (\mathbf{M}_{\text{nume} \times \text{nume}}^{(k)})^{-1} \cdot \Delta\rho_1^{(k+1)}. \quad (16)$$

Step 7: correct the resistivity distribution $\rho^{(k+1)}$ of the sensitive field according to equation (17), calculate the forward problem to obtain the calculated value $\mathbf{v}^{(k+1)}$ of the boundary voltage of the sensitive field, and substitute it into equation (14) to obtain $E^{(k+1)}$. If $E^{(k+1)} < b_{\text{estf}}$, replace the minimum error value b_{estf} of the algorithm and the optimal value $\mathbf{b}_{\text{estr}}$ of the resistivity distribution of the sensitive field with $E^{(k+1)}$ and $\rho^{(k+1)}$, respectively, and return to Step 5; otherwise, return to Step 5 directly:

$$\rho^{(k+1)} = \rho^{(k)} + \Delta\rho^{(k+1)}. \quad (17)$$

Using the abovementioned modified Newton–Raphson image reconstruction algorithm, the reconstructed images are shown in Figure 5 using a PC with a CPU of Intel (R) Core(TM) i7-4510U 2.60 GHz and 8 GB RAM.

And, the image correlation coefficient, image relative error e , and absolute error AE are shown in Tables 2–4, and their expressions are shown in Equations (18)–(20), respectively.

$$\rho = \frac{\sum_{i=1}^L (\hat{\mathbf{g}}_i - \bar{\mathbf{g}}) \cdot (\mathbf{g}_i - \bar{\mathbf{g}})}{\sqrt{\sum_{i=1}^L (\hat{\mathbf{g}}_i - \bar{\mathbf{g}})^2 \sum_{i=1}^L (\mathbf{g}_i - \bar{\mathbf{g}})^2}}, \quad (18)$$

$$e = \frac{\|\mathbf{g} - \hat{\mathbf{g}}\|_2}{\|\mathbf{g}\|_2} \times 100\%, \quad (19)$$

where $\mathbf{g}$ and $\hat{\mathbf{g}}$ are the setting value of electrical conductivity distributions of tissues and organs in the FEM of the human lung ERT and corresponding calculated value by solving the inverse problem with the modified Newton–Raphson algorithm, respectively, and their averaged values are $\bar{\mathbf{g}}$ and $\bar{\hat{\mathbf{g}}}$, respectively, L is the number of triangular finite elements for dividing the sensitive field of the ERT, and i is the finite element number:

$$AE = \frac{1}{5} \sum_{i=1}^5 \left| \frac{\rho_i - \hat{\rho}_i}{\rho_i} \right|, \quad (20)$$

where ρ_i and $\hat{\rho}_i$ ($i = 1, 2, 3, 4, 5$) are conductivity values of the tissues and organs (including the heart, spine, fat, and normal and pathological lung tissue) in the FEM of the human lung ERT and that obtained by solving the inverse problem with the modified Newton–Raphson algorithm.

It can be seen from Tables 2–4 that, at electrode angles of 1.8750 degrees, 3.7500 degrees, 5.6250 degrees, 7.5000 degrees, 9.3750 degrees, 11.2500 degrees, and 13.1250 degrees, respectively, the average values of image correlation coefficients are 0.8691, 0.8467, 0.8567, 0.8259, 0.8388, 0.8162, and 0.7744, the average values of image relative error are 40.8608%, 44.1065%, 42.5599%, 44.2302%, 42.5519%, 44.6313%, and 49.4449%, and the average values of absolute errors are 0.1112, 0.1180, 0.1030, 0.1500, 0.1386, 0.1518, and 0.1551. According to Figure 5, the quality of reconstructed images is the highest when the electrode angle is 1.8750 degrees.

Base on the comprehensive comparison in the aspect of the morbidity degrees of the sensitivity matrix and Hessian matrix, the uniformity of sensitivity distribution, and the quality of reconstructed images at electrode angles of 1.8750 degrees, 3.7500 degrees, 5.6250 degrees, 7.5000 degrees, 9.3750 degrees, 11.2500 degrees, and 13.1250 degrees, the optimised result of the electrode angle is 1.8750 degrees.

FIGURE 3: Continued.

(c)

(d)

FIGURE 3: Continued.

FIGURE 3: Continued.

FIGURE 3: Schematic diagram of sensitivity distribution.

TABLE 1: Comparison of different parameters of the corresponding sensitivity matrices.

Parameters	1.8750 degrees	3.7500 degrees	5.6250 degrees	7.5000 degrees	9.3750 degrees	11.2500 degrees	13.1250 degrees
Maximum	0.0186	0.0192	0.0187	0.0192	0.0188	0.0189	0.0186
Minimum	-0.0035	-0.0029	-0.0026	-0.0025	-0.0025	-0.0025	-0.0025
P	6.3435	6.3314	6.3183	6.3003	6.2789	6.2507	6.2195

FIGURE 4: Configurations of the internal tissue and organ distribution of the FEM of the human lung.

FIGURE 5: Continued.

FIGURE 5: Continued.

FIGURE 5: Reconstructed images. (a) The electrode angle θ is 1.8750 degrees. (b) The electrode angle θ is 3.7500 degrees. (c) The electrode angle θ is 5.6250 degrees. (d) The electrode angle θ is 7.5000 degrees. (e) The electrode angle θ is 9.3750 degrees. (f) The electrode angle θ is 11.2500 degrees. (g) The electrode angle θ is 13.1250°.

TABLE 2: Comparison of image correlation coefficients.

Distribution configuration	1.8750 degrees	3.7500 degrees	5.6250 degrees	7.5000 degrees	9.3750 degrees	11.2500 degrees	13.1250 degrees
1	0.8672	0.8374	0.8481	0.8450	0.8531	0.8260	0.7763
2	0.8677	0.8531	0.8724	0.8604	0.8874	0.8250	0.8009
3	0.8248	0.8253	0.8034	0.7468	0.7615	0.7523	0.6922
4	0.8544	0.8396	0.8481	0.8103	0.8102	0.7658	0.7421
5	0.9115	0.8804	0.8928	0.8491	0.8557	0.8736	0.8180
6	0.8890	0.8444	0.8754	0.8439	0.8646	0.8545	0.8168
Average value	0.8691	0.8467	0.8567	0.8259	0.8388	0.8162	0.7744

TABLE 3: Comparison of image relative error (%).

Distribution configuration	1.8750 degrees	3.7500 degrees	5.6250 degrees	7.5000 degrees	9.3750 degrees	11.2500 degrees	13.1250 degrees
1	42.3959	44.9342	44.2451	41.9743	40.5445	44.6119	49.8141
2	40.9719	42.8324	39.3069	39.6172	35.6991	44.3858	47.6893
3	46.4351	47.8764	48.9121	51.8914	50.8653	51.0591	56.3174
4	42.5821	45.7429	43.8716	46.1569	46.4721	50.4642	52.6781
5	34.8015	39.3734	38.2171	43.1964	41.9310	37.2090	45.0135
6	37.9780	43.8795	40.8065	42.5448	39.7991	40.0577	45.1568
Average value	40.8608	44.1065	42.5599	44.2302	42.5519	44.6313	49.4449

TABLE 4: Comparison of absolute errors.

Distribution configuration	1.8750 degrees	3.7500 degrees	5.6250 degrees	7.5000 degrees	9.3750 degrees	11.2500 degrees	13.1250 degrees
1	0.1129	0.0719	0.0591	0.1259	0.1398	0.1573	0.1545
2	0.0901	0.1018	0.0809	0.1386	0.1228	0.1185	0.1636
3	0.1558	0.1783	0.1739	0.2023	0.1897	0.1562	0.1650
4	0.0809	0.1142	0.0860	0.1256	0.1065	0.1467	0.1619
5	0.1219	0.1641	0.1214	0.2009	0.1582	0.1905	0.1370
6	0.1053	0.0776	0.0970	0.1070	0.1145	0.1413	0.1484
Average value	0.1112	0.1180	0.1030	0.1500	0.1386	0.1518	0.1551

4. Conclusion

To improve the accuracy of solving the inverse problem for human lung ERT, first, the FEM for human lung ERT was set up based on prior knowledge. On this basis, the results were compared and analysed in the aspects of the morbidity degrees of sensitivity matrix and Hessian matrix, the uniformity of sensitivity distribution, and the quality of reconstructed images at electrode angles of 1.8750 degrees, 3.7500 degrees, 5.6250 degrees, 7.5000 degrees, 9.3750 degrees, 11.2500 degrees, and 13.1250 degrees, respectively, and the optimisation of electrode width was obtained. In the future, by adjusting the position of the outermost triangular finite element node, the number of array electrode widths can be increased. On this basis, the number of array electrodes, array electrode widths, and data acquisition mode can be comprehensively optimised.

Data Availability

The data used to support the findings of the study can be obtained from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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