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Measuring Lung Resistivity Using Electrical Impedance Tomography

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Abstract—We propose the use of electrical impedance tomography (EIT) imaging techniques in the measurement of lung resistivity for detection and monitoring of apnea and edema. In EIT, we inject currents into a subject using multiple electrodes and measure boundary voltages to reconstruct a cross-sectional image of internal resistivity distribution. We found that a simplified, therefore fast, version of the impedance imaging method can be used for detection and monitoring of apnea and edema. We have showed the feasibility of this method

through computer simulations and human experiments. We speculate that the EIT imaging technique will be more reliable than the current impedance apnea monitoring method, since we are monitoring the change of internal lung resistivity. However, more study is required to verify that this method performs better in the presence of motion artifact than the conventional two-electrode impedance apnea monitoring method. Future work should include experiments which carefully simulate different kinds of motion artifacts.

INTRODUCTION

It is desirable to have a relatively accurate and noninvasive method for ventilation monitoring. Long-term ventilation monitoring is applicable in many clinical and research situations. Even through direct methods of ventilation monitoring such as spirometers or flowmeters are accurate, they are not convenient and practical for long-term or home monitoring. Accurate noninvasive ventilation measurement is useful for apnea detection in infants and adults, tidal volume measurement, ventilation monitoring in intensive care units, and lung monitoring for patients suffering from respiratory complexes. This method is also very useful for sleep studies where the breathing pattern and tidal volume, as well as ECG and EEG signals, are recorded during sleep.

The most widely used method of lung volume measurement uses two-electrode impedance pneumography and is notorious for problems arising from motion artifacts. AAMI technical information report [2] and Akbarzadeh [1] described current apnea monitoring methods and their problems. Harris *et al.* [5], [6] demonstrated the feasibility of applied potential tomography (APT) for monitoring pulmonary function. They used a dynamic imaging technique of electrical impedance tomography (EIT) using 16-electrode belt and backprojection between equipotential lines method [3]. They showed a close correlation between impedance index computed from dynamic resistivity images and volume of inspired air measured by spirometer. By using a fast algorithm where they computed the impedance index of a one-pixel region-of-interest (ROI), they could monitor respiration with a sampling rate of five impedance indexes per second. However, they did not examine the effect of motion artifact on the performance of their system. The fundamental limitation of their method is the fact that their system only responds to changes in resistivities and cannot be used to quantify the amount of air or water content present in the lung.

In this paper, for apnea monitoring and also for the detection and monitoring of edema, we propose using the static imaging technique of EIT, which uses many electrodes to reconstruct a cross-sectional static image of the resistivity distribution. Webster [9] described EIT from the discussion of tissue resistivity to image reconstruction algorithms and possible applications.

In applying EIT static imaging techniques to apnea monitoring, we designed a finite element mesh of the thorax using known structural information [4]. On the mesh, we identified a few different areas including the lungs, the heart, the spine, and other tissues. All elements belonging to one of the areas were constrained to have the same resistivity value. We found that the image reconstructed using this constrained mesh exhibits changes of lung resistivities during breathing.

Even though this method provides information about the change of lung resistivities during breathing, it has not been demonstrated that this method is better than the conventional method in terms of signal-to-artifact ratio. Further study is required to investigate the effect of motion artifacts on the lung resistivity estimation using this technique.

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ALGORITHM FOR APNEA MONITORING USING MULTIPLE ELECTRODES

Static EIT Image Reconstruction Algorithm

When we inject current into the thorax, the boundary voltage is a nonlinear function of the resistivity distribution of the thorax. Once we fix the number and locations of the electrodes and the patterns of injection current, the boundary voltage can be expressed as follows:

$$\hat{v} = \hat{f}(\hat{\rho}) \quad (1)$$

where $\hat{v}$ is a column vector of the boundary voltages on the electrodes, $\hat{\rho}$ is a column vector of the resistivity distribution of the thorax and $\hat{f}$ is a mapping from $\hat{\rho}$ to $\hat{v}$.

In static EIT imaging, we construct a finite element model of the thorax by dividing the thorax into many small elements (pixels) and assume homogeneity within each element. For a certain fixed model resistivity distribution ρ , we solve the Laplace equation using the finite element method (FEM) to compute the model boundary voltage v . When we inject P patterns of current into the model, we need to solve the following linear systems of equations (P times the number of repeated solutions of the same linear system of equations for each v_i due to the corresponding c_i).

$$\mathbf{Y}[v_1, \dots, v_P] = [c_1, \dots, c_P] \text{ or } \mathbf{YV} = \mathbf{C} \quad (2)$$

where $\mathbf{Y}$ is an $N \times N$ admittance matrix, $\mathbf{V}$ is an $N \times P$ voltage matrix, $\mathbf{C}$ is an $N \times P$ current matrix and N is the number of nodes in the finite element model. Since each v_i contains all node voltages of the model including internal nodes, we extract boundary node voltages from v_i 's with the following transformation:

$$\mathbf{v} = \mathbf{T}[v_1, \dots, v_P] \text{ or } \mathbf{v} = \mathbf{TV}. \quad (3)$$

Now we can define a function f which gives all model boundary voltages for a fixed model resistivity distribution ρ as follows:

$$\mathbf{v} = f(\rho). \quad (4)$$

In the static EIT image reconstruction, we inject optimal patterns of currents [7], [8] into a real object and measure the boundary voltage $\hat{v}$ and we also compute the model boundary voltage v due to the same injection current using the FEM. Then, we can define the following nonlinear programming problem:

$$\min_{\rho} \Phi(\rho) = \frac{1}{2}(f(\rho) - \hat{v})^T(f(\rho) - \hat{v}). \quad (5)$$

Then we change the resistivity distribution of the model ρ so that the error between the measured boundary voltage from the real object and the computed boundary voltage from the model is minimized. Fig. 1 shows the block diagram of our EIT system.

Yorkey *et al.* [14] developed the modified Newton-Raphson method to solve (5). Woo *et al.* [11] improved the method using Hachtel's augmented matrix method. This improved Newton-Raphson method is more robust and produces better static images by reducing the undesirable effects of the ill-conditioned Hessian matrix.

Application to Apnea Monitoring

In determining lung resistivity, we can use EIT imaging techniques with some modifications. First, since we are not interested in imaging, we do not need to use many elements (pixels). Second, we can fully take advantage of known *a priori* structural information about the thorax. Therefore, we propose the following method to determine lung resistivity.

Fig. 1. Block diagram of EIT system.

1) We assume that the resistivities of the lung change during breathing due to the changes in the amount of air in the lung.

2) We construct a finite element model of the thorax as shown in Fig. 2 using *a priori* structural information [4]. We group all elements belonging to each organ by forcing them to have the same resistivity value. Here we assume that there are no large variations in resistivity values within one organ or group of similar tissues. For example, the model boundary voltage can be expressed as follows:

$$\mathbf{v} = f(\rho_{ll}, \rho_{rl}, \rho_h, \rho_{sb}, \rho_m) \quad (6)$$

where ρ_{ll} , ρ_{rl} , ρ_h , ρ_{sb} , and ρ_m are the resistivities of left lung, right lung, heart, spine and bone, and muscle, respectively.

3) We apply the above described static EIT image reconstruction algorithm using these four resistivity values as variables. Since we have only a small number of variables, we can compute the values of these resistivity variables quickly.

4) We monitor the changes in the resistivity values of the lung ρ_{ll} and ρ_{rl} during breathing by reconstructing a sequence of resistivity images.

5) The changes in the resistivity values of the lung should be greater than a certain value in order not to sound an alarm.

We designed the finite element mesh shown in Fig. 2. Elements are grouped together and forced to have the same resistivity values within each group. Figs. 3 and 4 show simulation results using this method. Though the true images were perfectly reconstructed after six iterations with the error value of zero, the images after the first iteration are reasonably good.

Assuming that the resistivity of the lung changes from 800 $\Omega \cdot \text{cm}$ to 1600 $\Omega \cdot \text{cm}$ during breathing as in Figs. 3 and 4 and we take measurements at times $T_1, T_2, T_3, \dots$, which correspond to minimal or maximal lung resistivity values, we can generate a sequence of images as shown in Fig. 5. If the time difference between two successive images is small compared to the fundamental frequency of ventilation, we can monitor the ventilation by examining the values of the lung resistivity inside the thorax using this method. We believe that this method is more accurate than the current impedance apnea monitoring method since this method provides information about lung tissue whereas all of the current two-electrode impedance apnea monitoring devices use information predominantly from the chest-wall movements and not from resistivity variation in lung tissue.

The feasibility of this algorithm for real-time monitoring of lung volume is also highly dependent upon the amount of required com-

Fig. 2. A finite element mesh designed for apnea monitoring. Elements shaded with the same pattern are grouped together.

Fig. 3. Two-dimensional simulation results of the improved Newton-Raphson algorithm which simulates the state of the lung with a large amount of air in it. True resistivity distribution was reconstructed with zero error after six iterations.

putation and the computational power of the computer system to be used. We will discuss the computational topics in the next section.

Computational Complexity and Real-Time Monitoring of Lung Resistivity

Let N be the number of nodes of the finite element mesh, R the number of pixels (resistivity variables), P number of injection patterns, E number of electrodes, and $M = EP$ number of voltage measurements. Let τ be the total number of nonzeros in the sparse matrix $\mathbf{Y}$, then

$$\tau = O(N^{1+\gamma}) \quad (7)$$

where in most cases $\gamma \approx 0.4$ [12]. Then, the minimal number of arithmetic operations involved in the sparse LU factorization and

Fig. 4. Two-dimensional simulation results of the improved Newton-Raphson algorithm which simulates the state of the lung with a small amount of air in it. True resistivity distribution was reconstructed with zero error after six iterations. Scale of resistivities shown in Fig. 3.

Fig. 5. A sequence of images during computer simulated real-time monitoring of lung volume. Scale of resistivities shown in Fig. 3.

substitution to solve the linear system of equations are $O(N^{1+2\gamma}) = O(N^{1.8})$ and $O(N^{1+\gamma}) = O(N^{1.4})$, respectively. Then, the total amount of computation for one iteration of the improved Newton-Raphson algorithm C_T is

$$C_T \approx O(N^{1.8}) + PRO(N^{1.4}) + O((M + R)^2). \quad (8)$$

The computation time for one iteration of this method is fast enough to compute the resistivity values once every second using a 16-MHz Macintosh II if, for example, $N < 500$, $P < 4$, $R < 6$, and $E < 32$. However, if we use a faster PC or an add-on board containing an accelerator or parallel processor, e.g., a Transputer, we will be able to sample at the 5-Hz rate required for infant apnea monitors or use a finer finite element mesh (bigger N and R), more measurement data (bigger P and E), or more iterations to increase the accuracy in determining lung resistivity.

Application of Static EIT Imaging Technique Including Variable Geometry

In the previous method, we assumed the geometric shape of the thorax does not change during breathing. Thus, we fixed the shape and size of the finite element model for image reconstruction. However, observation of *in vivo* ventilation suggests that the geo-

metrical shape changes significantly with ventilation in some sections of the thorax. Therefore, we may reduce the error due to the geometrical shape change by including geometric variables. Specifically, we regard the voltage response of a given current as a function of both the resistivity distribution and the geometrical shape:

$$v = f(\rho_{ll}, \rho_{rl}, \rho_h, \rho_{sb}, \rho_m, r_l, r_t, \dots) \quad (9)$$

where r_l and r_t are vectors of coordinates of nodes which belong to the boundary of the lung and the thorax in the finite element model.

However, the solution of (5) using (9) will require a computation of the Jacobian matrix which includes sensitivities of boundary voltage due to geometry as well as resistivity of each element. We have not yet implemented this method and the usefulness of the geometrical variables is unknown.

HUMAN EXPERIMENTS

We placed a belt with 32 equally spaced compound electrodes [13] around the thorax of one normal male adult. Then, using the mesh shown in Fig. 2, we reconstructed images shown in Fig. 6 by the improved Newton-Raphson method. The resistivity of the lungs changed from 1263 $\Omega \cdot \text{cm}$ for maximal inspiration to 1181 $\Omega \cdot \text{cm}$ for maximal expiration. Fig. 7 shows reconstructed images using 16 equally spaced compound electrodes and the resistivities of the lungs are 1223 $\Omega \cdot \text{cm}$ for maximal inspiration and 1187 $\Omega \cdot \text{cm}$ for maximal expiration. Thus, images using 32 compound electrodes have a larger dynamic range of resistivities and distinguish the different breathing states better than images using 16 compound electrodes. This is because an increased number of electrodes yields an increased data input and the ability to more faithfully reproduce the resistivity distribution. Images using 16 simple electrodes even failed to correctly produce larger resistivity for normal expiration than minimal expiration [13]. This is because compound electrodes have smaller electrode-skin interface impedance and yield an increased ability to more faithfully reproduce the resistivity distribution.

Witsoe and Kinnen [10] measured changes in canine lung resistivity at 100 kHz as a function of the inspired air. Their results showed a lung resistivity of 705 $\Omega \cdot \text{cm}$ for a collapsed lung and 1608 $\Omega \cdot \text{cm}$ for a total of 700 cm^3 of inspired air and the standard deviation was 180 $\Omega \cdot \text{cm}$. Compared to their results, the changes of lung resistivities in Figs. 6 and 7 are small. The underestimation of the changes in lung resistivity is mainly due to the fact that we used a two-dimensional model though actual currents flow in three dimensions. A three-dimensional finite element model of the thorax should produce a larger dynamic range of lung resistivities due to the smaller sensitivity of the boundary voltages to three-dimensional elements.

DISCUSSION

Even though we have demonstrated the feasibility of the EIT static imaging technique as an apnea monitoring method, there are still many questions to be answered. Without any motion artifact, current impedance apnea monitoring devices work quite well. Therefore, the most important question is the performance of this method when motion artifacts are present. We speculate that the EIT imaging technique described above will be more reliable than the current impedance apnea monitoring method since we are monitoring the change of internal lung resistivity. However, this should be verified by experiments which carefully simulate different kinds of motion artifacts. It will be difficult to place a large number of electrodes on a new born or small baby and have the electrodes

Fig. 6. Change of the lung resistivity for different breathing states using 32 compound electrodes on the human thorax. (a) Maximal inspiration. (b) Normal inspiration. (c) Normal expiration. (d) Maximal expiration.

Fig. 7. Change of the lung resistivity for different breathing states using 16 compound electrodes on the human thorax. (a) Maximal inspiration. (b) Normal inspiration. (c) Normal expiration. (d) Maximal expiration. Scale of resistivities shown in Fig. 6.

function for 24 h or more. A possible solution would be to extend existing straps containing two or three conductive rubber electrodes into a stretchable vest containing multiple conductive rubber electrodes.

We also need to study the performance of this method as a function of N , R , P , and E and determine the optimal values for N , R , P , and E . The optimal locations of electrodes on the thorax of a subject and the patterns of injection current are also important to maximize the signal-to-artifact ratio.

CONCLUSIONS

In order to yield an instrument that will provide a more accurate measurement of lung volume in the presence of movement artifacts and increase the reliability of infant apnea monitors, we propose the use of EIT imaging techniques. We demonstrated the feasibility of the method from computer simulations and also experiments on one human. We speculate that this method will be more accurate than the current impedance apnea monitoring method since this method provides information about lung tissue whereas all of the current two-electrode impedance apnea monitoring devices use information predominantly from the chest-wall movements and not from variation in lung tissue resistivity.

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Minimal Repetition Evoked Potentials by Modified Adaptive Line Enhancement

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Abstract—A new method called modified adaptive line enhancement (MALE) to obtain evoked potentials with minimum stimulus repetitions is described. The theory of MALE is developed and the assumptions made are tested and shown to be adequate in the case of brainstem auditory evoked potential. The signal distortion are characterized and methods to alleviate the problem are developed. Using the weighted exact least squares lattice algorithm, the MALE method is implemented and applied to real data. It is shown that brainstem auditory evoked potential can be obtained with less than 40 repetitions using MALE method compared to 2000 required if conventional ensemble averaging method is used.

INTRODUCTION

Ensemble averaging is the traditional method of extracting evoked potentials from background noise [1]. For short-latency evoked potentials such as brainstem auditory evoked potentials (BSAEP), as many as 2000 realizations have to be ensemble averaged to obtain adequate noise suppression [2]. The variability of

the neuronal pathway being stimulated due to habituation, fatigue, etc. along with a desire to follow the dynamic changes in the pathway necessitates the reduction of number of stimuli presented to the subject to a minimum, ideally one [2]. Many methods employing optimal and/or adaptive filtering methods to achieve reduction in the number of repetitions required have been attempted. Due to the complexity of the data being processed, none of these methods have been successful to such a degree that they are in routine use.

The information contained in the prestimulus interval is put to good use in reducing the variance of the noise by the so-called predictor-subtractor-restorer method [3]. However, this method has not been found very useful in the application discussed in the literature for visual evoked potentials. We have developed a method which utilizes the prestimulus data and employs modern adaptive filter algorithms to produce significant reduction in noise variance in the BSAEP case. This reduces the number of repetitions of the stimuli to a minimum and only a small number of realizations are ensemble averaged to obtain the evoked potentials—hence, the name Minimal Repetition evoked potential (MR ep).

Our method is a modification of the well-known Adaptive Line Enhancement (ALE) used in digital signal processing when signal is narrow-band and noise is wide-band [4], [5]. The method of modified adaptive line enhancement (MALE) we propose can be used if the signal is intermittent and its time of occurrence is known. In other words, the MALE method can be applied if data are available with the signal (i.e., signal plus noise) and without the signal (i.e., noise only).

MODIFIED ADAPTIVE LINE ENHANCEMENT (MALE)

In the prestimulus interval in the evoked potential paradigm, noise alone is present and in the post-stimulus interval, both signal and noise are present. For the moment, consider the pre-stimulus interval. Assume that data observed at time t , y_t , is a stationary autoregressive (AR) time series. y_t contains all the correlated (in time) electrophysiological noise (filtered e.g., e.m.g., etc.) and filtered instrumentation noise. Using the unit delay operator, D , and a polynomial in D , $A(D) = 1 - a_1 D - \dots - a_k D^k$, we can write the AR time series, y_t as

$$y_t = \frac{1}{A(D)} w_t \quad (1)$$

where w_t is a white Gaussian time series. Equation (1) can be written as

$$y_t = \sum_{j=1}^k a_j y_{t-j} + w_t = \hat{y}_{t|t-1} + w_t \quad (2)$$

$\hat{y}_{t|t-1}$ is the one-step forward prediction of y_t given $y_{t-1}, y_{t-2}, \dots, y_{t-k}$ and w_t is the forward prediction error [6]. Taking variances of both sides of (2),

$$\begin{aligned} \text{Var}[w] &= \text{Var}[y] - \text{Var}[\hat{y}] \\ \text{or } \text{Var}[w] &\leq \text{Var}[y] \end{aligned} \quad (3)$$

If the time series is "predictable" (i.e., correlated in time), $\text{Var}[w] < \text{Var}[y]$. In our application, we will show that y_t is highly autocorrelated. Therefore, $\text{Var}[w] \ll \text{Var}[y]$. From (1), prediction error can be written as

$$w_t = A(D)y_t \quad (4)$$

In the prestimulus interval, when noise alone is present, $A(D)$ can

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