NEURAL-FUZZY MODELLING OF LUNG VOLUME USING ABSOLUTE ELECTRICAL IMPEDANCE TOMOGRAPHY

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Abstract: Electrical Impedance Tomography (EIT) has been the subject of intensive research since its development in the early 1980s by Barber and Brown at the Department of Medical Physics and Clinical Engineering, Hallamshire Hospital in Sheffield (UK). In particular, pulmonary measurement has been the focus of most EIT related research. One of the relatively recent advances in EIT is the development of an absolute EIT system (aEIT) which can estimate absolute values of lung resistivity and lung volumes. However, there is still active research in the area of validating and improving the accuracy and consistency of the aEIT estimation of lung volumes towards characterising the system as suitable for clinical use. In this paper we present a new approach based on Computational Intelligence (CI) modelling to model the „Resistivity - Lung Volume" relationship that will allow more accurate lung volume predictions. Eight (8) healthy volunteers were measured simultaneously by the Sheffield aEIT system and a Spirometer and the recorded results were used to develop subject-specific Neural-Fuzzy models able to predict absolute values of lung volume based only on absolute lung resistivity data. The developed models show improved accuracy in the prediction of lung volumes, as compared with the original Sheffield aEIT system. However the inter-individual differences observed in the subject-specific modelling behaviour of the „Resistivity-Lung Volume" curves suggest that a model extension is needed, whereby the modelling structure auto-calibrates to account for subject (or patient-specific) inter-parameter variability.

1 INTRODUCTION

Electrical Impedance Tomography (EIT) has been a topic of interest for researchers including clinicians due to its ability to offer a non-invasive, radiation-free monitoring. EIT aims to generate cross-sectional images of the studied subjects based on measurement of surface electrical potentials resulting from an excitation with small alternating currents via an array of equally-spaced electrodes attached to the surface of the thorax at about 4-5 cm above the xyphoid process (Barber, 1984 and Brown, 2003).

EIT has been used to generate images of various parts of the human body, nonetheless, the lung ventilation measurements have always been regarded as one of the areas which seem to have possible benefits from the development of EIT. In 1985 Brown et al suggested the use of EIT in lung imaging and ventilation monitoring in what was the first summary of possible clinical applications for this technique (Brown, 1985). For most of the recent EIT studies, the focus has been on the changes

in impedance with time (relative/functional EIT), instead of the absolute values. The new absolute impedance tomography takes this a step further, by not only looking at the changes in impedance during the respiratory cycles, but also producing absolute (as opposed to relative) values of impedance that can be compared to normal or reference values. Indeed, a multi-frequency system was developed in the mid 1990‟s to calculate the absolute impedance (Brown, 1995) and subsequently calculate an absolute volume measurement of the lung. The method of determination of lung absolute resistivity (Brown, 2002) is based on a 3D finite difference model of the thorax developed from CT cross sections of a normal subject (G. Zubal, 1994) and scaled to take into account the geometry of the chest (circumference and ellipse ratio) of a particular subject. The elements in the model were assigned fixed resistivity values in the range 1-80 Ω-m depending on their anatomical location (fat, muscle, bone, blood or lung) in the CT images. The modeled data are then compared with the real measurements over a pre-determined region of interest for values of the lung resitivities between 3 and 80 Ω-m. The value of lung resistivity, which minimizes the mean difference between these data sets, is returned as the value of the absolute lung resistivity, an EIT image is reconstructed by filtered back projection (Barber, 1987). As lung resistivity is a function of the frequency of the applied current, at high frequency, when the capacitive reactance of the cell membranes are reduced virtually to zero, the lungs consist of just two equivalent electrical components; air with almost infinite resistivity and lung tissue with an almost homogeneous resistivity determined by that of the intracellular and extra-cellular fluids (Barber, 2005). If these resistivities are known, then it becomes possible to calculate both lung density and air volume using a Cole equation (Brown and Mills, 2006). The complexity of aEIT in the absolute lung air volume has more or less contributes to some problems in getting a consistent and accurate measurement from the system.

A significant amount of research has so far been devoted to investigating the feasibility of EIT to assess the level of lung ventilation in comparison with the volume of air measured with spirometer. Harris *et al.* (1987) showed the proportional relationship between the lung volume change and lung resistivity using EIT imaging and confirmed the system‟s ability to assess the level of lung ventilation. Their work identified a close correlation between an impedance index computed from dynamic resistivity images and volume of inspired air measured by a spirometer. In 1988 research confirmed a high correlation ($r > 0.95$) between the change in lung impedance and volume of air inspired in four healthy subjects while at rest and on a bicycle ergo-meter (Harris, 1988). The study demonstrated that real-time EIT ventilation measurements of lung volume were possible to an accuracy of +/- 10% of the spirometer values. The posture of the subject was again an area of interest, with data recorded in five subjects in both seated and supine positions, showing an impedance variation of between -3.8% and +9.5% from the former to later posture. Nicolas *et al.* (2005) elicited a parametric model of the relationship between EIT and total lung volume with the aim at facilitating inter individual comparisons of EIT images by providing volumetric scale in place of the usual arbitrary units scale. The lung volume changes predicted by the model were compared to the volume changes measured by spirometry. The model was able to predict the lung volume changes with 9.3% to 12.4% accuracy. These studies confirmedthe fact that there exists significant correlation between the variable derived by EIT and lung volume changes measured with spirometer and it is possible to model associated relationship.

In this paper, the relationship between absolute resistivity from the aEIT system and the lung volume measured from spirometry were studied based on the data from 8 healthy volunteers. Two data-driven models were developed; the first model (AEIT) was built for the relationship between data from aEIT to mimic the behaviour of the system in producing the absolute lung air volume from absolute resistivity, while the second model (EITSPIRO) was developed for the relationship between spirometry lung air volume and absolute resistivity. An Adaptive Neural-Fuzzy Inference System (ANFIS) network design (Jang, 1993) is used in this modelling exercise. Finally, a new hybrid model structure is proposed for selecting the best model to predict the absolute lung air volume to be used in the aEIT system.

2 STUDY PROTOCOL

2.1 Subjects

A total of eight (8) healthy subjects (males) participated in this study. The subjects‟ height, weight, circumference and ellipse ratio were measured and recorded. The studied subjects‟ information is shown in Table 1.

Table 1: The anthropometric information of the subjects

Subject	Gender	Height (cm)	Weight	Circum (cm)	Ellipse ratio
1	M	170	80	95	1.51
2	M	170	67	88	1.38
3	M	171	60	83	1.58
4	M	186	113	109	1.39
5	M	184	93	104	1.53
6	M	191	79	95	1.53
7	M	168	66	90.5	1.36
8	M	171	62.5	88	1.45

2.2 Equipments and tools

A disposable tape measure was used to measure the subjects‟ chest circumference. “Mitutoyo Absolute Digmatic” callipers were used to measure the subjects‟ chest; measurements were taken of chest width and depth in order to calculate an ellipse ratio.
The aEIT data were acquired via the Sheffield Mk 3.5 absolute EIT system. The Mk3.5 aEIT (Figure 1) uses eight AgCl ECG type electrodes to inject small alternating currents at 30 frequencies typically within the range 2 kHz to 1.6 MHz and records the resulting potentials at a rate of 25 frames.s^{-1}. The computer user interface to control the Mk3.5 system is written in MATLAB, and is able to display real-time images.

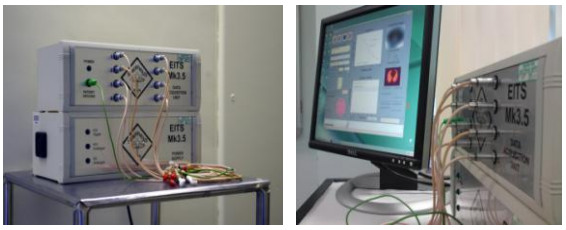


Figure 1: The Sheffield EIT Mk 3.5.

2.3 Data acquisition

2.3.1 Spirometry and EIT measurements

Eight (8) skin electrodes were attached around the circumference of the chest, and connected to the EIT data acquisition unit. Ideally the electrodes were attached in a horizontal plane 5cm above the xiphoid process, and equally spaced around the circumference (Figure 2).

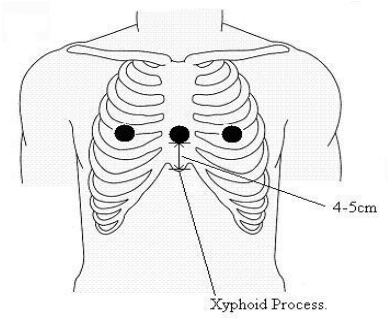


Figure 2: The level of the EIT electrode array in the frontal plane.

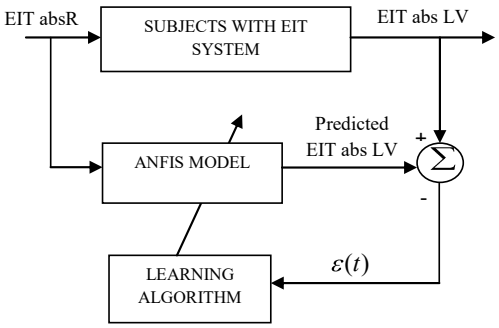
The subjects were simultaneously breathing through the spirometer tube (SensorMedics) while attached to the Mk 3.5 aEIT system. The data were measured using adjacent drive and receive combinations of electrodes, connected to the data acquisition unit. A 60 sec recording of data were performed involving quiet breathing and maximum inspiration and expiration manoeuvres in sitting position. The acquired EIT data were then resampled using MATLAB according to the spirometry sampled data. The spirometry sampled data represent the instantaneous changes in lung volume (relative to residual volume).

3 DATA-DRIVEN MODELLING USING ANFIS

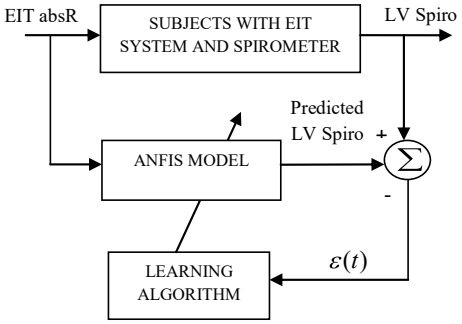
Neural-Fuzzy modelling falls under the umbrella of Computational Intelligence (CI) modelling and can be used as a non-linear method for mapping a certain number of inputs to a certain number of outputs. This non-linear mapping can be learned from process data using various algorithms. The architecture used in this study is the Adaptive Neural-Fuzzy Inference System (ANFIS) consisting of a set of TSK-type fuzzy IF-THEN rules. The TSK-type fuzzy model was proposed by Takagi, Sugeno and Kang (Sugeno and Kang, 1988, Takagi and Sugeno, 1985) in an effort to develop a systematic approach to generate fuzzy rules from a given input-output data set. A typical fuzzy rule in Sugeno fuzzy model has the form:

$$\text{IF } x \text{ is A and } y \text{ is B THEN } z = f(x,y)$$

Where A and B are fuzzy sets in the antecedent, while $z = f(x,y)$ is a crisp function in the consequent. The ANFIS architecture is used as the facet of the modelling structure in order to map the aEIT data. In the first part of the „Results‟ section (4.1) only the aEIT data recordings are used to develop a data-driven model of the „Lung Resistivity – Lung Volume‟ (Lung R-V) relationship. This model will map the non-linear relationship „Lung R-V‟ by „imitating‟ the aEIT system‟s physical equations (Brown, 2002). This modelling structure is shown in Figure 3a.



(a)



(b)

Figure 3: (a) Model structure for AEIT model. (b) Model structure for EITSPIRO model. EIT absR =EIT absolute resistivity. LV Spiro= spirometry lung volume, EIT absLV= EIT absolute lung volume and $\varepsilon(t)$ = error between actual and predicted lung volume

In the second part of the „Results" Section (4.2) the Spirometry recordings are used along the aEIT data in an effort to „bypass" the aEIT system"s lung estimations using physical equations, hence attempting to predict directly lung volumes using the Spirometry data for a reference. The Spirometry data (relative lung volume) were converted to absolute lung volume data by estimating the Residual Volume (RV) of all eight volunteers using Body Plethysmography in the Royal Hallamshire Hospital, Sheffield UK. Figure 4 shows an overview of the various modelling structures.

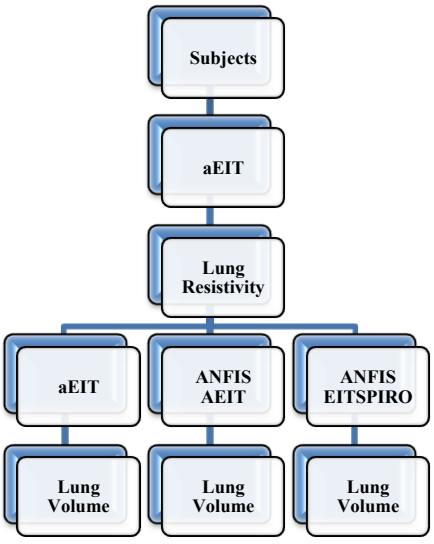
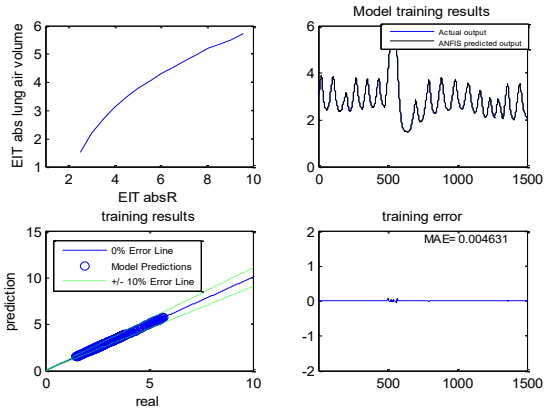


Figure 4: An overview of the various modelling structures

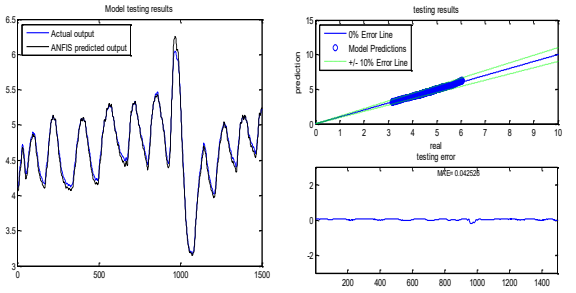
4 RESULTS AND DISCUSSIONS

4.1 AEIT models training and testing results

The first type of model built in this study is the AEIT model which is based on data of absolute EIT resistivity and absolute lung air volume (as measured by the aEIT system) obtained from 8 healthy subjects in a sitting position. The aEIT mk3.5 system uses a number of non-linear equations to infer absolute lung volumes from resistivity data. Example of such equations include the Cole-Cole equation (to link a frequency spectrum to resistivity data), the Nopp model (to link lung tissue resistivity as a function of lung volume) (Brown and Mills, 2006), and a number of population mean models of lung weight based on gender. Most of these equations are empirical/theoretical and introduce uncertainties and inaccuracies in the final estimations of lung volumes. The objective of first modelling exercise is to mimic the behaviour of the physical/theoretical/empirical equation based on data from these 8 healthy subjects. The 8 subject-specific AEIT models results are shown in Figure 5. Table 2 shows the modelling performance results. Root mean square error (rmse), mean absolute error (mae%), correlation coefficient (cor.) and standard deviation of the error (eSD) were used as the performance indices. As shown in Figure 5, the AEIT model can predict the absolute lung air volume with a good accuracy in training (99.8%) and testing (95%). The current modelling results show that ANFIS is a good modelling method to learn the relationship between the absolute resistivity and absolute lung air volume as currently described in the aEIT system. However, such a model would inherit all the inaccuracies of the aEIT system in the estimation of lung volumes, as shown in (Panoutsos, 2008 and Tunney, 2008) and detailed in the following paragraph.



(a)



(b)

Figure 5: (a) The AEIT model training results (b) The AEIT model testing results

Table 2: (a) The models training fit results. (b) The models testing fit results

	rmse	mae%	eSD	Cor
S1	0.0026	0.0635	0.0026	1
S2	0.0081	0.149	0.0081	0.9999
S3	0.0043	0.102	0.0043	1
S4	0.0206	0.2779	0.0206	0.9999
S5	0.0152	0.4739	0.0152	0.9998
S6	0.0343	0.5429	0.0343	0.9993
S7	0.0054	0.2561	0.0054	1
S8	0.0039	0.068	0.0039	1
mean ± SD	0.012 ± 0.0	0.242 ± 0.2	0.012 ± 0.0	1.000 ± 0.0

(a)

	rmse (mean ± SD)	mae%(mean ± SD)	cor(mean ± SD)
S1	0.487 ± 0.32	0.27 ± 0.13	0.889 ± 0.13
S2	0.244 ± 0.27	0.192 ± 0.19	0.966 ± 0.07
S3	0.159 ± 0.16	0.159 ± 0.16	1 ± 0.00
S4	0.319 ± 0.24	0.29 ± 0.24	0.990 ± 0.01
S5	0.279 ± 0.4	11.27 ± 8.1	0.996 ± 0.0
S6	0.070 ± 0.1	9.478 ± 5.3	0.999 ± 0.0
S7	0.408 ± 0.7	9.539 ± 7.5	0.769 ± 0.4
S8	0.089 ± 0.0	5.012 ± 2.8	0.997 ± 0.0

(b)

Even though that the AEIT models show good performance, in reality the models also inherit the errors of the aEIT system when we compare the lung volumes with real Spirometry data. Figure 6 shows an example of the absolute EIT lung air volume as compared to the real lung air volume as measured by Spirometry. As it can be seen in Figure 6, there is a clear difference between the aEIT estimated lung volume and the real lung volume measured using Spirometry (20.7% average error for all eight subjects) Hence it can be concluded that the ANFIS model is capable of mapping such non-linear behaviour very accurately, but some inherited modelling errors (included in the aEIT equations) do not allow for a very accurate lung volume modelling. It is possible to „bypass" the aEIT equations and attempt to model the lung volume directly from volumetric measurement data using Spirometry as described in the next section.

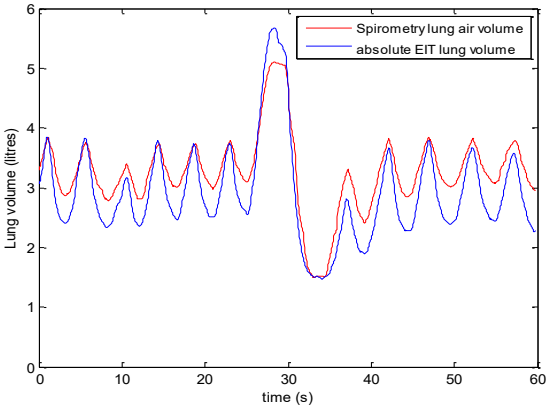
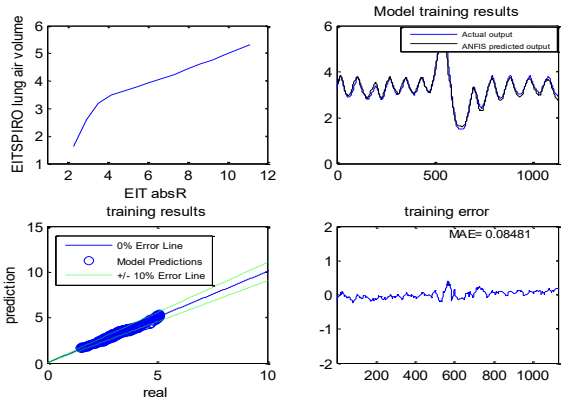


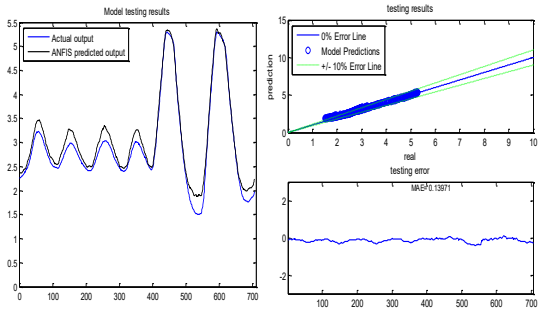
Figure 6: The plot of actual absolute EIT lung volume and actual spirometry lung air volume

4.2 EITSPIRO models training and testing results

The second type of model built in this study is the EITSPIRO model which is based on data of absolute EIT resistivity and Spirometry lung air volume obtained from 8 healthy subjects in sitting position. The models are designed to predict the spirometry lung air volume directly from the absolute EIT resistivity as obtained from the EIT Mk 3.5 system. The 8 subject-specific EITSPIRO models results summarised in Table 3 and a representative example of one subject is shown in Figure 7. Root mean square error (rmse), mean absolute error (mae%), correlation coefficient (cor.) and standard deviation of the error (eSD) were used as the performance indices.



(a)



(b)

Figure 7: (a) The EITSPIRO model training results (b) The EITSPIRO model testing results

Table 3: (a) The models training fit results. (b) The models testing fit results

	rmse	mae%	eSD	Cor
S1	0.0951	1.6843	0.0952	0.9968
S2	0.2325	4.8183	0.2326	0.9718
S3	0.1025	1.1356	0.1026	0.9962
S4	0.6068	13.6506	0.607	0.9417
S5	0.1553	4.1812	0.1554	0.9867
S6	0.3583	6.4761	0.3585	0.821
S7	0.0951	2.6752	0.0952	0.9893
S8	0.1245	2.7523	0.1245	0.9714
mean ± SD	0.221 ± 0.2	4.672 ± 4.0	0.221 ± 0.2	0.959 ± 0.1

(a)

	rmse (mean ± SD)	mae%(mean ± SD)	cor(mean ± SD)
S1	0.655 ± 0.42	14.17 ± 8.56	0.931 ± 0.09
S2	4.094 ± 3.39	51.77 ± 13.47	0.837 ± 0.13
S3	0.733 ± 0.42	16.73 ± 9.68	0.925 ± 0.08
S4	1.465 ± 0.63	36.39 ± 16.07	0.864 ± 0.10
S5	0.953 ± 0.28	20.13 ± 7.71	0.915 ± 0.09
S6	1.267 ± 0.51	28.47 ± 9.33	0.912 ± 0.04
S7	2.178 ± 1.78	25.84 ± 12.56	0.828 ± 0.13
S8	2.381 ± 2.19	24.9 ± 8.63	0.856 ± 0.12

(b)

The EITSPIRO modelling results show that this modelling structure can predict the lung air volume with good accuracy in training (95.3%). When testing a subject-specific model on a different subject the average performance deteriorates to about 72.7% accuracy. While this is an acceptable performance it clearly demonstrates the effect of inter-individual difference and the need for subject-specific models (or patient-specific in the case of clinical use). Figure 8 shows the lung R-V relationship for the eight subjects as predicted by the ANFIS model. There is a common trend between the different subjects (resembling the Nopp model/equation), but it also shows how different this behaviour can be between subjects. Figure 9 shows the lung volume of one healthy subject as measured by Spirometry, estimated by aEIT and predicted by the ANFIS model. It is clear that the ANFIS model best predicts the subject"s lung volume as compared with the aEIT system. The advantage of the ANFIS model is clear, however to be able to implement this on a real system the model would need some type of calibration, for every time it is used, to account for the inter-individual differences of the subjects.

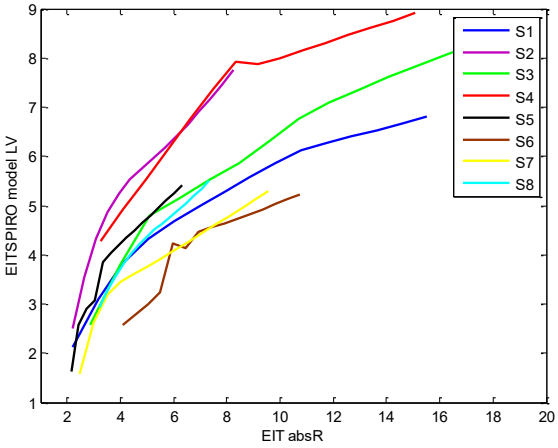


Figure 8: The plot of lung R-V relationship for the eight subjects as predicted by the ANFIS model

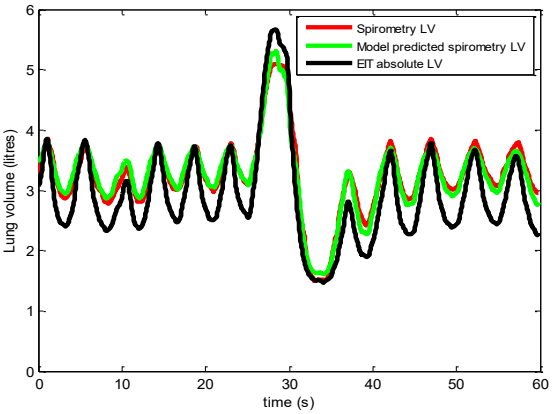


Figure 9: The plot of EITSPIRO model predicted lung air volume, actual absolute EIT lung volume and actual spirometry lung air volume

5 CONCLUSION AND FUTURE WORK

Electrical Impedance Tomography was developed in the early 1980s and it has since shown real potential to being exploited for clinical use (bedside monitoring in the Intensive Care Unit - ICU). Recent developments in the field of absolute EIT demonstrate how one may use it to estimate absolute values of lung volumes which are key to any on-line EIT based monitoring system. However, the current system can be further improved, in particular in the area of lung volume estimation accuracy. In this study a Neural-Fuzzy modelling structure is used to model the relationship between the lung absolute resistivity and lung volume (lung R-V). Data recordings were used from eight (8) healthy subjects in a sitting position in order to train the models. It was shown that the modelling structure can model very accurately the aEIT lung volume estimation, although this method forces the model to „inherit" the inaccuracies associated with the aEIT theoretical and empirical equations. In a different approach, it was also shown how one can model the lung R-V by „bypassing" the physical equations and directly model the lung volume based on real volumetric measurements using Spirometry (to record relative volume) and Body Plethysmography (to record lung Residual Volume). To our knowledge this is the first data-driven model developed to describe the behaviour of lung Resistivity-Volume in the absolute EIT system. The developed models show a very good agreement between the real data and the model predictions, however high inter-individual differences were also noted. Although, on an individual basis, each ANFIS model (patient-specific) outperforms the current aEIT system"s lung volume estimations. In clinical science, inter-patient variability is endemic; this is why it is of the opinion of the authors that an extension to the presented approach is needed, whereby the model auto-calibrates to account for inter-individual differences between patients. The new modelling structure should be able to classify the „patient-type" based on the R-V behaviour curves and adjust the predictions accordingly.

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