Mapping Lung Water Signal Distribution on Human Chest and Predition of Lung Water Content

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***Abstract*—Measuring lung water change is invaluable for monitoring patients with heart failure and pulmonary diseases and assessing their responses to the treatment. Sensors for such measurement have been developed in Hawaii Advanced Wireless Technologies Institute (HAWTI) and clinical trials have been carried out. In this paper, we use numerical simulations to obtain the signals received by the sensors as a function of lung water content and sensor locations on the human torso. The data are interpolated to obtain a finer distribution of signals on the chest. The higher resolution data are used to train the support vector regression (SVR) machine to establish a prediction model for lung water content as a function of received signal and location of the sensors. The interpolation and SVR methods can save significant simulation time and will be used for building a database for lung water prediction for various human torsos.**

Keywords—sensors, pulmonary diseases, biomedical applications, numerical simulation, machine learning

I. Introduction (*Heading 1*)

Chronic heart failure and pulmonary hypertension are among the leading causes of hospitalization, health care costs and deaths in the United States [1]. To manage these groups of diseases, we need a reliable way of early detection and assessment of the changes in lung water (CLW) content. Our team has developed and patented the Cardio-Pulmonary Stethoscope (CPS) [2-4] technology which is a novel, "Chest Patch" sensor system for non-invasive and continuous monitoring of vital signs and CLW. The device uses low cost 915 MHz RF transceivers and is FCC safety standard compliant. Excellent results were obtained in recent clinical trials at Queen' s Medical Center in Honolulu, Hawaii. Results with fluid removed during hemodialysis treatment showed correlation factor of r = 0.82 to 1, while PCWP measurements of heart failure patients had correlation factor of r = 0.52 to 0.97 [4]..

To better understand the CPS signals as a function of lung water content as well as the locations of the CPS sensors on the chest, we have employed full wave electromagnetic field simulations (using HFSS) in addition to the clinical testing. We try to use these simulated results to establish a database where different sizes and details of human torsos/organs and other aspects that affect the CPS signals will be included. With this database, it is possible to relate the measured CPS signal to the lung water content in real time.

One of the difficulties in building such a database is the long computational time for simulating the CPS signals. For example, using HFSS, it takes about 3 to 6 hours to obtain the signal for one sensor location with one lung water content on a one human torso model. To have a database of practical value, many sensor locations, many water content levels, and many human torso models (sizes, details of organs, etc.) are needed. The overall simulation time for building the database is therefore enormous and not feasible for most developers.

To relieve the simulation burden, we resort to data interpolation and machine learning techniques. Based on limited number of simulations, we can generate many more CPS signals through interpolation which are then employed to train a support vector regression (SVR) machine to predict the lung water content. Our results show that it is possible to significantly reduce the computational burden without sacrificing reliability. Furthermore, we've found that not all sensor locations are equal, which can be useful in practice.

II. Simulation Arrangement and the Otained Data

A 4 cm x 4 cm grid is created on the human chest on which sensors will be placed and received signals will be recorded. In Fig. 1, two rows of such sensor locations are illustrated. At each location the transmitting and receiving sensors are mounted on the chest side by side as shown in the figure.

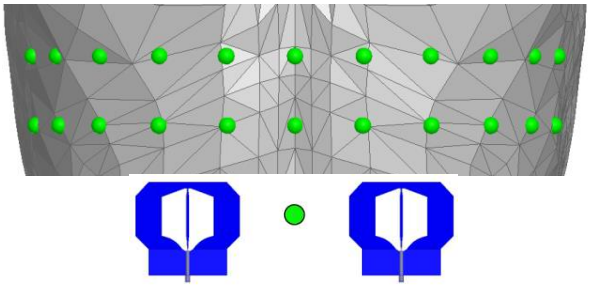


Fig. 1. (Top) Two rows of sensor locations represented by green dots on the human chest and superimposed on the chest model in HFSS; (Bottom) The transmitting and receiving sensors.

The S_{12} values are recorded for each sensor location and the phases of S_{12} will be used for prediction of the lung water content. Three lung water content values are considered: 20 %, 30 %, and 40 %. The phases along the bottom row of sensor locations for these three levels of water content are shown in Fig. 2.

Due to the geometry of the human chest, we need to place the sensor on a grid illustrated in Fig. 3. Note that the less number of sensors in the upper body is because in the torso model the arms are overlapping with the sides of the upper chest.

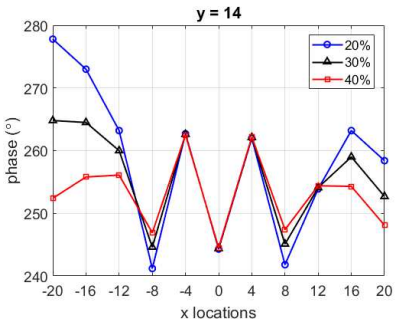


Fig. 2. Phases of the S_{12} on the bottom row of 11 sensors for three levels of lung water content.

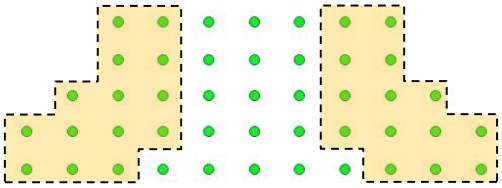


Fig. 3. The grid for 45 sensor locations.

III. Interpolation and SVR Training

To obtain more data for water contents and sensor locations, we interpolate the phases on the coarse grid in Fig. 3 using bi-linear interpolation for sensor locations and linear interpolation for water content.

Since the phase values on the center part of the sensor locations are not distinguishable for the three water contents (see Fig. 2), interpolation in that area does not work properly and they are ignored in this paper. Thus, we only use the left and right sensor in the shaded areas in Fig. 3.

Using interpolation, we can have as many data points as possible and they can be used for training the machine (10,000 data points are generated in all examples in the paper). The vector support regression (SRV) is employed for building the prediction model. The open source library, scikit-learn [5], is used where SRV is a built-in function. After some parameter tuning in the SRV function, we are able to obtain very good prediction results.

IV. Prediction Accuracy

In this section we present the prediction results of the left side area in Fig. 3. It is noted that different sub-regions in this area also provide different prediction accuracy. Based on our trials, we divide the area into 5 regions, as shown in Fig. 4.

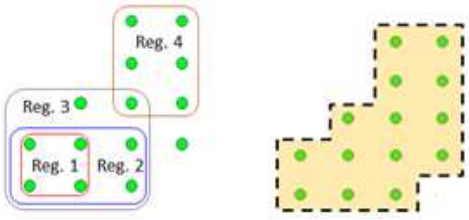
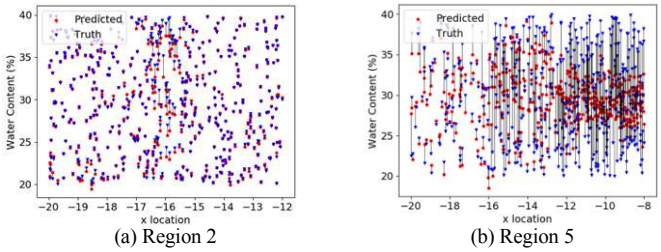


Fig. 4.

Left: Regions 1-4; Right: Region 5.

In Fig. 5, the predicted water contents and the ground truths are presented for Regions 2 and 5. A line is drawn between each pair of the truth and the predicted water content. The standard deviations of the prediction errors and the scores (function to estimate the quality of the prediction model) for all the regions are shown in Table 1. It can be seen that for regions 1 and 2, the prediction accuracy is very good while it is not good at all in regions 4 and 5. The region 3 has a borderline accuracy.



(a) Region 2 (b) Region 5

Fig. 5. The predicted and ground truth for water contents in Region 2.

TABLE I. Lung Water Content Prediction Accuracy

Region	1	2	3	4	5
Standard Dev. (%)	0.068	0.430	2.980	5.000	4.949
Score	0.99986	0.99445	0.73388	0.24015	0.23467

V. Conclusion Future Work

A procedure to interpolate the limited simulation phases of S_{12} on a grid on the chest surface is developed to save computational time. The interpolated data are then used to train a learning machine for the prediction of lung water content as a function of sensor locations and received signals (phases of S_{12}). It is shown that different regions of the chest can have different properties of the signals and have different water content prediction accuracy. This is of practical value because it indicates that data collected by the sensors at different chest locations are not equally useful.

Our future work includes more simulations for human torsos with different sizes and different levels of details of the organs. A database and a prediction model will be established for the prediction of lung water content. These models will be ultimately applied in practice after clinical verification and improvement using clinical data.

References

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