A Time Delay based Approach to Enhance Lung Diseases Diagnostic

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Abstract: We are dealing with Chronic Obstructive Pulmonary Disease (COPD), using a new methodology based on Passive Time Delay Technique (PTDT). Lung sounds were recorded using a multichannel stethoscope on 28 healthy subjects and 20 COPD patients. The sensors were distributed on the posterior and anterior chest wall. During recordings, all participants were breathing at matching airflow rates. Calculated time delay (TD) was identified for inspiration phase and an average TD value was provided after three repetitive measurements for each inspiration phase. TD computed in COPD patients: 440 ± 87 % ($P < 0.05$) was remarkably greater than time delay computed with normal subjects: 160 ± 10 % ($P < 0.05$). Results were presented as mean ± SD, standard deviation of time delay in ms. Significant P values ($P < 0.05$) were indicated using Wilcoxon test. Preliminary results are very encouraging to develop this technique and enhance COPD monitoring.

1 INTRODUCTION

Gas propagation in complex pathways of the respiratory system is accompanied by the spreading of lungsounds that can be collected in various regions of the thorax. Moreover, lung sounds are usually mixed with heart sounds and tissues sounds, caused by any change of the chest movements, during respiratory cycles.

Generally, purely lung signals are highly correlated with mechanical gases vibration along the different pathways as it was mentioned by (Meirav, 2009) and (Kraman, 1984), in their studies. Additional noisy signals must be filtered before dealing with lung signal analysis.

Capturing lung signals using a multichannel stethoscope was a frequent topic in the last decades. Multiple researches were developed using both active acoustic methods (AAM) and passive acoustic methods (PAM).

The AAM consists to transmit a low frequency sound into the chest via a loud speaker placed in the patient's mouth. Then, the delay and frequency response of the lung are used to understand the sound propagation inside the respiratory system (Wodicka, 1992).

The (PAM) consists on capturing lung sounds from different sites of the chest via digital stethoscope without introducing any external sounds. This dynamic method was used by different authors (Dellinger, 2008) and (Mor, 2007) to analyze the functional properties of different lung diseases. Different authors demonstrated that the PAM provides a better interpretation of the biological signals and adds more precision in the disease diagnose and decision making. One of the most recent of those authors is (Murphy, 2008).

In the present study we developed a time delay approach based on the PAM to understand the nature of lung sounds propagation in the case of an obstructive pulmonary disease such as COPD. We used the concept of time delay which is motivated by the fact that as the air travels from the mouth to different lung fields, the travel time will depend on the level of obstruction of the airways in the lung. By comparing the travel time of a healthy lung to that of lung with COPD, one can detect airways obstruction and the lung area where obstruction is occurring.

Abnormalities in the lung manifested by obstructions or restrictions are causing a local airflow perturbation inside the lung pathways providing an abrupt change in the lung signals recorded over multiple chest sites.

To estimate the time delay, the concept of signal correlation was used. We developed an extended approach for the time delay estimator that allows for the localization of affected lung zones.

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2 METHODOLOGY

The methodology adopted in this paper is based on a mathematical model build using experimental data.

2.1 Experiments

The experimental data is given from our own database. This database consists on lung sounds recorded from normal patients and COPD patients having all the following symptoms. Chronic bronchitis patients have sputum production such that cough and sputum for at least three months. Prior to recording lung sound phases, we collected information about patients such as name, age, sex, BMI, and thorax size.

Experimental measurements of lung sounds were tabulated in a database that contains smoking subjects and non-smoking subjects. All participants in these clinical experiments were asked to breathe three times and we recorded breath sounds for inspiration phases with time duration of 3 to 6 seconds. They were also instructed to hold their breath for few seconds and then to breathe easily before each new signal recording. Most information about patients was outlined in Table 1.

All participants' lung signals were recorded with an 8-channel stethoscope. This instrument was fully described in the following references (Alouani, 2011) and (Alouani, 2010). Figure1 show the multichannel stethoscope used in this study.

This instrument allowed recording lung sounds during breathing, which are proportional to the gas flow vibrations as postulated by (Kraman, 1984).

Table 1: Patient's criteria.

	COPD Patients	Normal Subjects
Number	20	28
BMI	32±5	42±8
Age	48±12	37±10
Gender (%Male)	80	64.285
Smoking (%)	60	25
Thorax Size (cm)	85±10	82±15
Weight (Kg)	83±14	78±16

The protocol of measurements was executed while subjects were seated. The eight sensors were distributed as follow; four acoustic sensors on the front of the chest and four acoustic sensors on the back. The protocol of recording sounds consists of three breathing cycles to unsure the consistency of the recording sounds. Recorded signals include inspiratory phases and have a time duration ranging between 3s and 6s. The goal here was to quantify the health state of patient's lung using a new time delay estimate (TDE) technique based on multichannel lung sounds recording.

Figure 1: Multichannel lung sound system, Capture of the detailed devices used in the multichannel sthetoscope (sensors, I/O box of connexion and DAQ server).

2.2 Theoretical Procedure

After collecting data, a preprocessing is used. The captured lung sounds were filtered using a variant of Sgolay filtering algorithm that we developed in references (Ayari, 2013) and (Ayari, 2012). We built an array of sensors with a distance adjusted according to the body size of the subject. The sounds were acquired via the multichannel stethoscope at a sampling frequency of 11 kHz.

Recorded lung sounds were then sent to computer storage for processing. Collected lung sounds, could then be displayed using appropriate Lab View software. Then, they are converted into a digital wave format and pre-processed so as to reduce noise effect.

The acquisition of captured lung sounds from multiple sites is conducted using a Lab View platform. We developed then a program using Matlab software to extract separate channels and to build the correlation matrix of the eight sensors, after a filtering process based on Sgolay algorithm. Further details about the algorithm that we developed are provided in the next section. A shot screen, of lung signals captured during processing phase.

We developed in this study, a new methodology that aims enhance COPD monitoring, based on time delay produced between captured lung sounds. We considered multiple time expanded lung waveforms recorded from eight positions on the chest. For the analysis and processing of time expanded waveforms, we built a matrix constituted with eight vectors corresponding to the different collected time

series of the eight signals.

As we are capturing airflow vibrations which are transformed into electrical signals, digitized further, and displayed on the shot screen as lung signals. Airflow vibrations provoked with abrupt airflow changes, (if any abnormality inside the lung tissues occurred) may amplify the lung signal differently and change its morphology. All depends on the distance traced by the airflow inside the lung pathways; those vibrations reached the sensors at different times. The correlation technique allows measuring this time difference denoted by time delay between captured lung signals.

To compare time delays between sensors, it is important to mention that any time delay estimator is constrained to operate on observations of a finite duration. Also a time delay estimator design is the available amount of a priori knowledge of the captured signals and their noise statistics. Thus, the common method to carry an estimate of the time delay is to compute the cross correlation function first between every couple of signals captured in two different sensors. General cross correlation function is used as a similarity measure function in signal processing, that is described by equation (1) in continues signals f (t) and g (t) and equation (2) in discrete time series.

$$(f * g)[n)] = \sum_{m=-\infty}^{\infty} f^*[m]g[n+m] \quad (1)$$

$$(f * g)[n)] = \sum_{m=-\infty}^{\infty} f^*[m]g[n+m] \quad (2)$$

Where f^* denotes the complex conjugate of the function f.

As described in (Knapp, 1976), time delay, estimated in the propagation between two signals across a microphone array is deduced after calculating cross correlation between both signals and pointing in time the point corresponding to maximum of the absolute value of the cross correlation function. This time delay (denoted by D) between both signals is defined as the argument of the maximum of the cross correlation function in Figure 2.

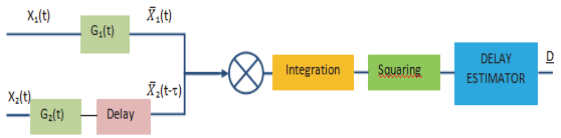

Figure 2: Received waveforms filtered, delayed, multiplied and integrated for a variety of delays until peak output is obtained.

$$D = \arg\max\big((f * g)(t)\big) \quad (3)$$

Signals emanating from a particular lung source mixed with a noise, at two spaced sensors can be modeled as follows:

$$x_1(t) = s_1(t) + n_1(t) \quad (4)$$

$$x_2(t) = \beta s_1(t + D) + n_2(t) \quad (5)$$

Where s_1 (t) is the lung signal, n_1 (t), and n_2 (t) are noise signals associated to both positions and β is a real parameter. It is assumed that the signal s_1 is uncorrelated with noise signals n_1 and n_2.

There are many theoretical approaches which are proposed by researchers to estimate the time delay using different refinement algorithms (Chan, 1980), in order to improve the precision in calculating this time delay based on cross correlation function. Some of them are available in the case of stationary signals; the others can be employed in slowly varying environments, where the characteristics of the signals and noise remain mainly stationary only for finite observation time interval T.

For lung signals, we summarized the description of the most important proposed algorithm applied in the case of nearly stationary signals in very small time intervals. Thus, the common method to carry an estimate of the time delay is to compute the general cross correlation function, which is given explicitly between two signals $x_1(t)$ *and* $x_2(t)$ by the following equations as mentioned by (Knapp, 1976):

$$R_{x1,x2}(\tau) = E[x_1(t)x_2(t-\tau)dt] \quad (6)$$

In the case of a small sized observation interval T, the cross correlation function takes the following form:

$$\hat{R}_{x1,x2}(\tau) = \frac{1}{T-\tau}\int_{\tau}^{T} x_1(t)x_2(t-\tau)dt \quad (7)$$

As far as it is necessary to carry accurate values of the estimate time delay D, it would be important to undergo a preprocessing of both captured signals $x_1(t)$ *and* $x_2(t)$. We consider the following filters denoted with G_1 (t) and G_2 (t) as it is illustrated by Figure 3. The outputs of the two filters G_1 (t) and G_2 (t) are denoted by $\bar{x}_1(t), \bar{x}_2(t)$. The objective of such filters is to smoothen and fine tune the cross correlation signal so that the maximum peak of this function can be sharply defined and therefore the time delay can also be accurately estimated.

The time shift yielding to the peak of the cross-correlation function is an estimate of the time delay D. Thus, to achieve a good and robust resolution of the time delay estimate, the input signals must be weighted.

Those weights are associated to several refinement techniques for example the technique proposed by (Chen, 2011) and the one due to (Kevin,

2006).Most techniques correspond to generalized cross correlation which is conceptually consisting on applying pre-equalization to the signals.

Performance of time delay estimation is strongly affected with noise associated to the captured signal and also to the length of the signal time interval. A low SNR with a relatively extended time interval are both key features for the performance of any refinement TD estimator algorithm. Most of the time delay refinement processors are expressed in the complex domain and their explicit form is done with a Fourier Transform relation. Thus, the cross power spectral density described by the Fourier transform relationship is given by equation (8) as mentioned by (Hyde, 1969) and (Georgiou, 1973).

$$R_{X_1X_2}(\tau) = \int_{-\infty}^{\infty} G_{x_1x_2}(f) e^{j2\pi f\tau} df \quad (8)$$

Generalized correlation between $x_1(t)$ and $x_2(t)$is given by:

$$R^{(ge)}{}_{\bar{X}_1\bar{X}_2}(\tau) = \int_{-\infty}^{\infty} \Psi_{ge}(f) G_{x_1x_2}(f) e^{j2\pi f\tau} df \quad (9)$$

$$\Psi_{ge}(f) = G_1(f) G_2(f) \quad (10)$$

Among the different existing weight functions (Kevin, 2006) and (Li, 2002) we selected the Phase Transform weight algorithm denoted by (PHAT).This algorithm uses a weighting function described with equation (11)**:**

$$\boldsymbol{\Psi_{PHAT}(f)} = \frac{\mathbf{1}}{\left|\boldsymbol{G_{x_1x_2}(f)}\right|} \quad (11)$$

In the case of non-correlated noise$G_{n_1n_2}(f) = 0$, the cross correlation will be expressed as:

$$\hat{R}^{(PHAT)}{}_{\bar{X}_1\bar{X}_2}(\tau) = \delta(t - D) \quad (12)$$

With:

$$\frac{\hat{G}_{x_1x_2}(f)}{|G_{x_1x_2}(f)|} = e^{j\theta(f)} = e^{j2\pi fD(f)} \quad (12a)$$

In fact, the phase transforms denoted with (PHAT) (Kevin, 2006), is the most used weighting algorithm and it is very interesting in the case of low noise to signal ratios. The PHAT weighting is the last step before calculating the estimate TD between both signals.

The different steps of our developed algorithm are illustrated by Figure 3 which indicates the main components of the TDE estimator as it is developed in this study. The weight function applied to two lung signals can be explicitly defined as:

$$\Psi\ (f) = \frac{1}{\left|\widehat{G}_{x_1x_2}(f)\right|} \quad (13)$$

And their final form of weighted cross correlation function is defined as:

$$\widehat{R}^{new}{}_{\bar{\bar{X}}_1\bar{\bar{X}}_2}(\tau) = \frac{1}{2\pi}\int_{-\pi}^{\pi} \frac{G_{x_1x_2}(f)}{\left|\widehat{G}_{x_1x_2}(f)\right|} e^{-j2\pi f} df \quad (14)$$

The PHAT weighting processor, used as the last step of TD estimation in our methodology, is justified since it is one of the best weighting functions to be selected in the case of non-stationary and noisy signals as indicated in (Georgiou, 1973). To emphasize the importance with applying such a procedure, we computed the time delay using a general cross correlation approach of two captured signals for one COPD patient. Then, we applied the procedure described above to estimate the time delay between those two signals, Figure 4. We concluded from Figure 4 (a) and Figure 4 (b), that our methodology has effectively strengthened the basic features of the signals. Figure 4 (b) shows clearly the difference between general cross correlation technique (a) and the enhanced correlation technique based on PHAT algorithm. From Figure 4 (b), one can distinguish clearly the improved accuracy, and the signals sharpness of the residual peak.

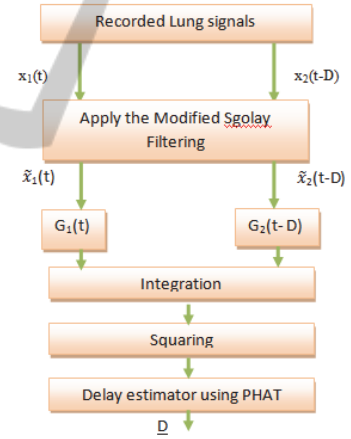

Figure 3: Diagram of TD using our approach.

3 RESULTS

After calculating the time delay between all couple of sensors, we saved the different time delay values in a matrix denoted by the time delay estimator matrix (TD_{ij}). In this matrix, we saved the time delay between two lung signals; among signals captured via the 8 sensors. Columns and rows are corresponding to the reference number of sensors. Each component of the matrix (TD_{ij}) corresponds to a TDE between sensor i and sensor j where i =[1,2,…,8] and j =[1,2,….,8].

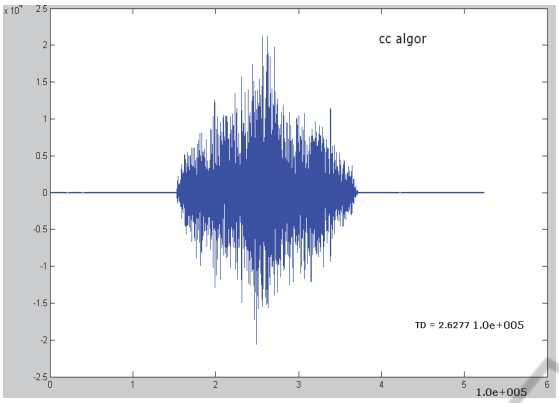

Figure 4: (a) General cross correlation algorithm of two signals for COPD (the x axis is done in samples), from recorded lung signals of sensor 1 and sensor 8 of patient number 3).

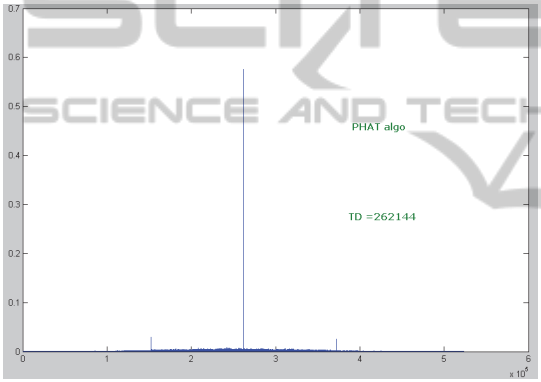

Figure 4: (b) Cross correlation of the same two signals using the PHAT algorithm (the x axis is done in samples), from recorded lung signals of sensor 1 and sensor 8 of patient number 3).

TD values calculated using sampling units are then converted into time delay measured in seconds. The final configuration of the correlation matrix is defined as illustrated by Table 2. Differences between recordings at different chest sites for the different patients were highly significant as revealed by statistical tests ($P < 0.001$). To accurately visualize the local TD results distribution, with a statistic interpretation we represented TD using 3D image in Figure 5forall patients. Such graphs can be very useful to localize and highlight the maximum peak of TDE values and also to visualize their distribution on the sensors Map. This representation allowed for localizing the chest zones where the rate flow is the lowest. Those chest zones may represent the most obstructed zones.

Table 2: The TDE matrix in (s) of the 3rd COPD Patient.

0	0,073	1,374	0	0,967	0,013	1,054	0,938
0,073	0	0,026	0,073	0,751	0,055	0,069	0,071
1,374	0,026	0	1,374	0,723	0,034	0,1	0,103
0	0,073	1,374	0	0,967	0,013	1,054	0,938
0,967	0,751	0,723	0,967	0	1,709	1,016	1,017
0,987	1,055	0,034	0,013	1,709	0	0,006	0,007
1,053	0,1	0,1	1,054	1,016	0,006	0	0,001
0,071	0,071	0,103	0,938	1,017	0,007	0	0

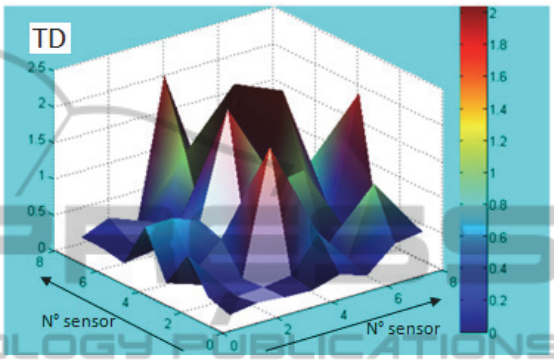

Figure 5: Example of 3D Map for a COPD patient.

4 DISCUSSION

For all the obtained TDE matrices, we observed that in every TDE matrix, among 64 measurements of time delay, few of them were equal to 0. Excluding the diagonal values which are forcibly equal to zero, we observed some symmetric zero delay values. i. e. in Table 2 we observed zero TD values between sensors (1-4 and 7-8). This fact means that time delay between lung signals captured at sensors 1 and 4 in one side and sensors 7 and 8 in another side are not significant. In all other combinations we found time delay values are varying asymmetrically. Two important facts have to be highlighted here; the first one is that we have registered few time delays which are above 1 second; this represents 26.28 % of the total measurements between the different sensors. The second fact is that a delay of 1.709 was found between sensors 5 and 6 for patient ref 3. This value was considered as a relatively high value and it may be used as an index of pulmonary disorder in the airway located between sensors 5 and 6.

TD values were describing respectively the chest zones when the probability of detecting damaged lung zone was important. As an example, in the particular case of the COPD's patient number 3, TD values presented a fluctuation between 0.013 s and

1.709 s which is the maximum delay recorded with this patient.

5 CONCLUSIONS

The development of new markers can be very helpful in enhancing lung diagnosis and update rules for early detection and treatment of COPD. In fact, both patients and doctors need to have simple indices that can describe briefly and accurately the health state of the patient's lung. That is the reason for which our team as many researchers groups are looking for new noninvasive biological markers, providing instantaneous measurable indexes.

The current study brings significant impact, as we have emphasized a particular attention to the applicability of multiple lung sounds captured via a multichannel stethoscope to enhance lung diagnosis and pulmonary disorders detection, identification and classification. As a future work, we suggest to study the effect of other parameters such as (BMI and gender) on the evolution of TD.

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