Automatic Lung Tidal Volumes Estimation from Tracheal Sounds

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***Abstract*— This paper presents a method to automatically estimate lung tidal volumes from the acoustic signals generated in the respiratory track. The signal is measured with an acoustic based sensor placed in the suprasternal notch. The method does not require any previous knowledge or modelling of the individual respiratory track, and relies on just one calibration parameter. The proposed algorithm is tested on 316 respiratory phases obtained from 4 volunteers. The subjects were simultaneously wearing a Wright respirometer which was used as a gold standard for comparison. Agreement between the two methods was assessed with Bland-Altman techniques. The results show the potential the technique has, integrated with a small acoustic sensor, for less-intrusive and even remote and/or continuous monitoring of lung tidal volumes.**

I. INTRODUCTION

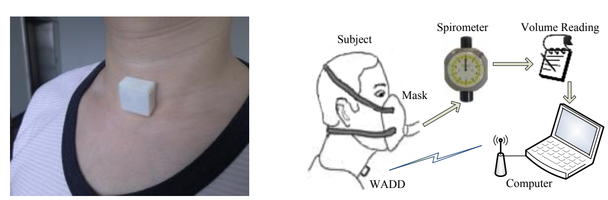
SINCE the invention of the stethoscope in 1816, extracting information about the lungs from sound signals generated in the process of respiration, has been a very active field of research. Specifically in the last few years, great progress has been made by groups like Moussavi's [1-5], Wodicka's [6-8], Gavrieli's [9-10] and others [11-13], on modelling respiratory flow using sound signals measured with acoustic sensors placed either on the chest or on the trachea. Quantitative measure of airflow is unarguably very useful due to its application in clinical areas which are relevant to a significant percentage of the population, such as diagnosis of sleep apnoea. There are however other respiration related parameters, such as lung volumes, that would also be of interest in a variety of contexts, and have not received as much attention. Lung volumes could in principle be extracted from airflow, as reported in [12], so should this approach be followed the quality of the model for quantitative airflow measurement would most certainly affect the accuracy on determining the lung volumes. However, when lung volumes are to be calculated by automatic means, accurate airflow determination is not the only factor affecting accuracy. The temporal characteristics of the signal and most specifically precise determination of integration times are also equally important. These integration times are not difficult to determine visually, mostly when dealing with artefact free segments of the signal. The problem becomes significantly more challenging when lung volumes have to be calculated automatically.

The main aim of this paper is to show the initial results of a simple method to automatically estimate lung tidal volumes using the outputs from a very small wireless acoustic based sensor placed on the suprasternal notch. The results also show that it is possible to obtain a good agreement with the values obtained using respirometry as the gold-standard, just by assuming a linear model with one calibration parameter.

II. ALGORITHM DEVELOPMENT

We first collected around 5-10 minutes of respiratory data from 4 subjects with a proprietary breathing monitoring technology (WADD) created by our group [14-15], and simultaneously with a Wright respirometer, for which subjects were wearing a mask. The WADD operation is based on sensing the acoustic signal generated by breathing with an MEMS microphone housed in a customized acoustic chamber, interfacing with also customized low power electronic blocks. The overall system is wireless, weighs less than 9g (including a biocompatible housing) and can operate continuously for over 48 hours. It attaches to the neck with a hydrocolloid adhesive approximately (2cm x 2cm) size. The preferred attachment is on the suprasternal notch, although this can be changed to the side of the neck in those subjects in which this location is not possible due to, for example loose skin or short neck. Apart from the raw signal, the WADD also provides automatic information about the respiratory signal, including its duration, presence or absence, temporal related parameters such as beginning or end of respiratory phases, and noise values. Fig. 1(a) shows a picture of one of the investigators wearing the current version of this device. Fig. 1(b) shows a schematic representation of the test set-up. Since the respirometer did not have an automatic output the readings were taken every cycle and recorded with a video camera. These readings included starting time, end time, initial volume, final volume, delta volume (difference between final and initial volumes) and average tidal volume (arithmetic mean of all delta volumes detected during the recording period). The subjects were instructed to remain in a sitting position, but they had freedom to do any kind of movement whilst being on that position. No particular effort was made to reduce environmental acoustic artefacts, so all the experiments were run under varying background noise conditions. Subjects were also instructed to try to change the depth of breathing, at any time they chose without warning.

In the initial experiment, the energy from the acoustic signal from expiration segments was automatically obtained from the WADD. This energy was plotted against the tidal volume values obtained from the respirometer. An illustration of the results obtained from one of the subjects is shown in Fig. 2. From the graph it can be observed that points with significantly different energies corresponded to similar tidal volumes, with a correlation coefficient R^2= 0.5567.



(a) (b)

Fig. 1: (a) Investigator wearing the WADD sensor. (b) Tidal volume measurement set-up.

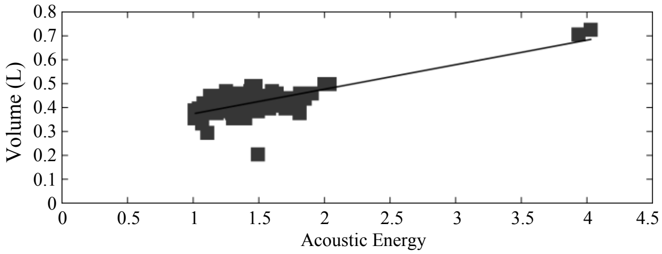


Fig. 2: Initial results: tidal volume values obtained from the respirometer versus acoustic energy integrated over underestimated duration (see Fig. 3 and related discussion for explanation).

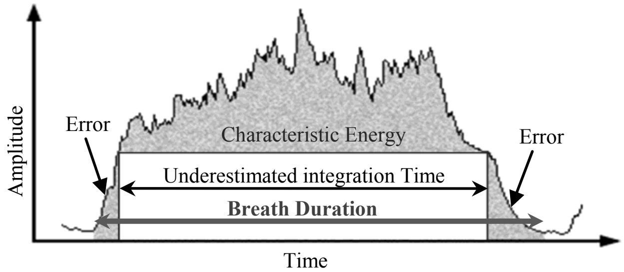


Fig. 3: Errors caused by underestimation of the integration time.

This was a positive but still poor result. By isolating points corresponding to a same tidal volume but very different energy, it was observed though that even when the energy was different within the overall signal bandwidth (100Hz to 2kHz), the scatter was greatly reduced if the calculation was restricted to a narrower band, more specifically 600Hz to 700Hz. The explanation for this is that, although there is an important breathing frequency content in the other bands, mostly in the lower one, the lower band also has stronger artefact signals frequency components. Hence, even in those cases in which the signal has a large signal to noise ratio and the breathing segments are easily identifiable, the remaining overlapping frequency components due to artefacts can significantly affect the energy calculation. This is not just because of the effect that they have in the overall power- which can in fact be very small, mostly if previous artefact rejection techniques have been applied- but rather because of the effect they can have in the automatic calculation of the integration time. Small variations in the estimation of start and end times can considerably affect the calculation of the energy. In the majority of cases, the energy is underestimated because part of the signal is not taken into account. A diagram illustrating this is shown in Fig. 3.

A second reason that was found to explain the lack of accuracy of the initial results was related to the offset observed in the fitting curve. That offset had no physiological explanation since absence of breathing flow should relate to absence of acoustic energy. The non-zero value accounted for the energy of signal artefacts originated from both other physiological as well as environmental sources; and also the electrical noise floor of the sensor and electronics around them. Although in the WADD artefact rejection is carried out at the hardware level which optimizes the signal to noise ratio, there are still residual signals that affect the energy calculation. In order to compensate for this, the algorithm would take periods of non-breathing (this was one of the outputs of the WADD), calculate the energy of the signal in those periods, and from there the power. This power would be multiplied by the duration of the signal during the breathing segment, and the resulting energy would be subtracted from the original energy in those segments. Just by doing this, together with the band restriction, the correlation coefficients increased to over 0.76 in all algorithm development cases (0.76-0.91), with the lowest correlation coefficient found in the experiment in which the offset had been the least successfully automatically removed, which proved the hypothesis that offset removal is needed.

A flow diagram of the final algorithm is shown in Fig. 4. The algorithm finds the energy of those segments of signals that have already been identified as breathing by the WADD, after filtering it, so that it is restricted to the 600Hz to 700Hz band, for the reasons explained above. The approach can be summarized as follows:

1) The input signal, obtained from the WADD is bandpass filtered and rectified (grey trace, Fig. 5).
2) The envelope of the signal is obtained (black trace, Fig. 5).
3) The algorithm searches the minimum of the envelope signal since the beginning of the current iteration and waits until it rises to a point ('A' in Fig. 5) as twice of the minimum or half of the maximum value from previous iteration (i.e. value of point 'C' from the previous segment, see step 5).
4) Once the envelope signal rises over twice the value of the minimum point calculated in 3, as long as the signal does not fall below twice the minimum, monitoring the change of the signal's slope, the algorithm searches a turning point as the integration starting point ('B' in Fig. 5) within the range of +/- 0.2s referred to the point when the signal becomes twice the minimum. The slope is evaluated with a running window of half this time. If there is no major change on the slope within that range, the start of integration is set to the point 0.1s prior to point 'A'.
5) After the integration starting point is confirmed, the algorithm looks for the maximum of the envelope signal and waits until it falls to a point ('C' in Fig. 5) half of the maximum value or point 'A'.
6) When the signal falls below the point 'C', the algorithm starts searching for the integration ending point ('D' in Fig. 5) by locating the position when the slope (same window length as step 3) of the envelope signal becomes positive.
7) The energy is obtained integrating the envelope of the signal between points 'B' and 'D'.
8) The power of the noise signal, which is also an output of the system, is filtered within the same frequency band and integrated within the same period of time.
9) The noise energy is subtracted from the value of the breathing signal energy obtained in step 7.

III. Results

The algorithm was tested on 316 breathing phases from 4 different subjects. The subjects were laying facing up. The first initial ten readings were used to calculate the gain and residual offset of the linear model via least mean squares fitting. The rest of the points were used to test the automatic performance. The results are shown in Fig. 6. It can be seen that in all cases the offset has been reduced to relatively low values, which illustrates that the noise cancellation strategy does work Without this the values of the offset was always larger than 0.3.

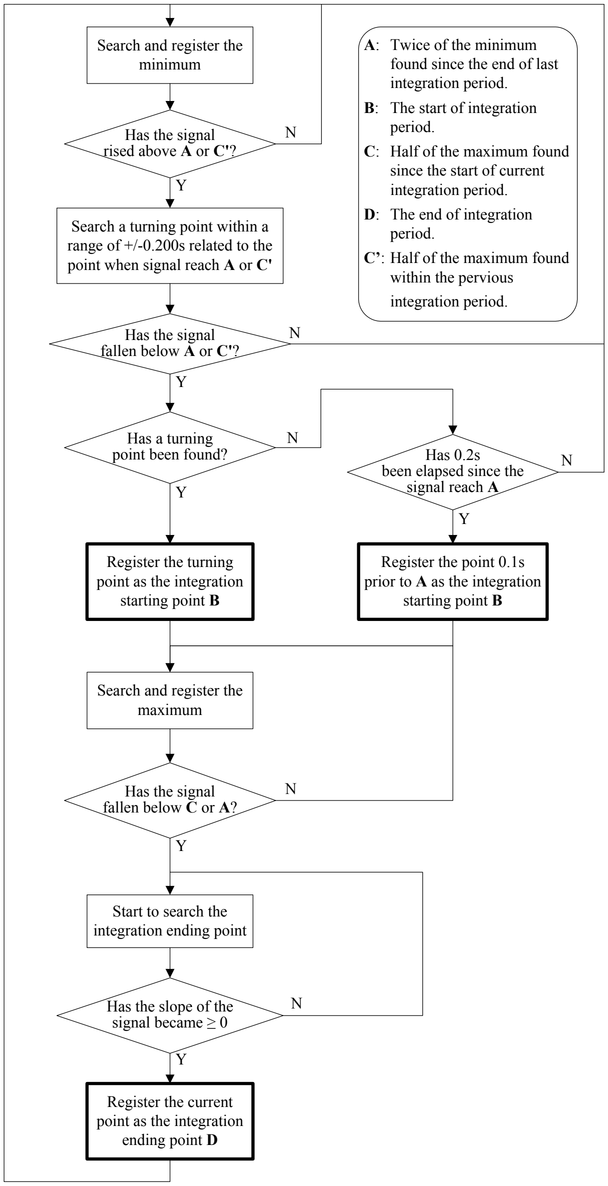


Fig. 4: Flow diagram of locating starting and ending point of integration period for tidal volume estimation.

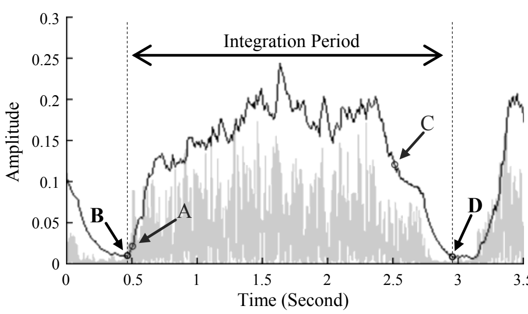


Fig. 5: An example of finding the correct integration period.

Statistical Analysis: Although the number of subjects in this study was low and therefore the method would need to be tested in a larger population to have significant power, Bland-Altman plots were obtained to explore whether this technique could have the potential to substitute the respirometer for quantification of tidal volumes. Fig. 7 shows the results for the four different subjects. Table I summarizes the values for the bias (residual offset), standard deviations and limits of agreement for the different figures. 96% of the points fall within the limits of agreement.

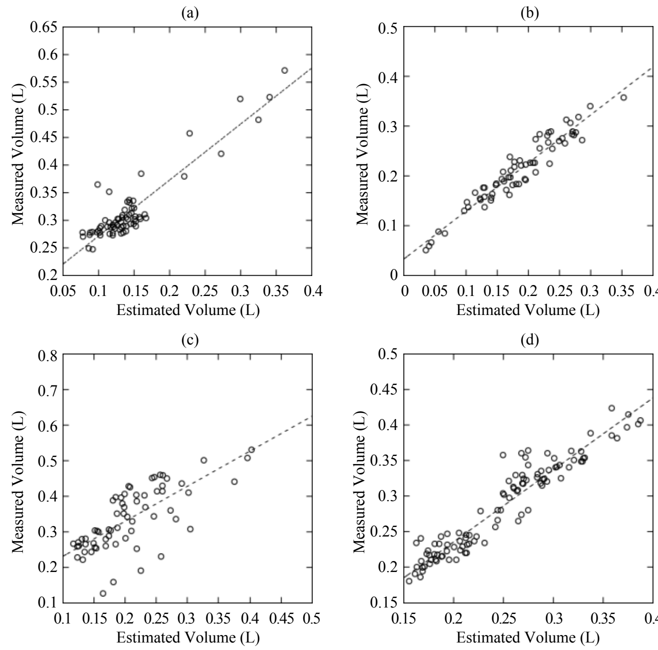


Fig. 6: Measured tidal volume obtained from the respirometer versus automatic estimated values.

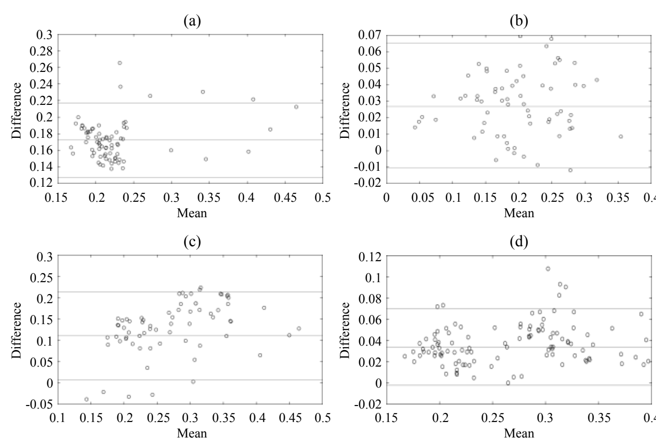


Fig. 7: Difference between measured tidal volume obtained from respirometer and its corresponding automatic estimated value against the mean of two methods.

Table I: Statistical results for automatic tidal volume estimation

Subject	Bias *d*	Standard deviation *s*	Limits of Agreement *d*+2*s*	*d*-2*s*
(a)	0.1711	0.0228	0.2167	0.1255
(b)	0.1289	0.0613	0.2515	0.0063
(c)	0.0277	0.0189	0.0655	-0.0101
(d)	0.0361	0.0195	0.0751	-0.0029

IV. Discussion

Although this is preliminary work it does show that it is potentially possible to automatically obtain lung volumes without a previous knowledge of flow, or characterization of physiological parameters, with just one calibration parameter (or maximum two if the residual offset is not acceptable). In agreement with literature, it was found that this parameter depended on whether the person was sitting, standing or laying down, although it remained constant if the person was in one fixed position. It was not necessary though for the person to be completely still, although the reason for this could be that the WADD output signals were already "artefact free". The results marginally improved if they were averaged over several breathing phases.

Even though the work presented on this paper mostly characterizes tidal volumes under normal or forced uninstructed shallow breathing, in principle there is nothing indicating that it would not be possible to extract other respiratory volumes and parameters [17] following the same method. For example, the Force Expiratory Flows (FEV) could be calculated integrating the signal during a fixed predetermined length of time according to the definitions of these volumes (whilst the subject follows the same instructions as in spirometry). FEV1 could be obtained by fixing the end time to the integration time to 1s after the start point. The Forced Vital Capacity (FVC) would be just the value obtained after the subject is instructed to force expiration. The Maximal Voluntary Ventilation (MVV) could be obtained integrating the whole signal (including respiratory pauses) for a fixed minute. The Force Expiratory Time (FET) could be obtained from the time distance between the two minima which determine the beginning and end of the integration period. The Slow Vital Capacity (SVC) would be the value of the tidal volume obtained while the person is asked to exhale slowly after slow maximum inhalation. Furthermore, because some of these volumes are "forced situations" during which the subject is asked to breathe in a particular way, they do not need to be obtained continuously, and they can also be obtained in a certain position for which the gain parameter is known. The WADD has the option of adding a time marker within the signal. This could be used to mark the time at which the test is taking place so that the reading is known to correspond to a particular type of parameter. This, together with flow values which could be obtained applying algorithms such as the ones presented in [2-5] on the same signal, could potentially have application for, amongst others automatic, early or remote diagnosis of COPD.

V. Conclusions

This paper has shown the initial results of an automatic method to determine tidal volumes from the acoustic signal obtained with the WADD breathing monitoring system. The algorithm uses as inputs signal segments that the WADD has already identified as either breathing phases of respiratory pauses, as well as noise values. The performance results of this algorithm show that it is possible to obtain a linear model that provides a good estimation of tidal volume based on the energy of the acoustic signal calculated within one particular band. However, this linear fitting can severely degrade if the start and end point of the signal used for integration are not properly determined, which makes the problem of automatic detection a non-trivial one. The algorithm proves to efficiently deal with this issue. It is also shown that by subtracting a noise related value the offset reduces to almost zero, which improves the accuracy of the model. This value is obtained by filtering and integrating the power of the noise signal provided by the WADD within the same band and in the same period of time.

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