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Heart Sounds Interference Cancellation in Lung Sounds

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Abstract: Several attempts have been made to achieve a quantitative analysis of lung sounds mainly for two purposes: a) an understanding of their genesis, and b) an insight of their changes with pathologies for medical diagnosis. Early studies involved the collection of acoustic information at several positions on the thoracic surface or at the extra-thoracic trachea with one up to four microphones, but with a non-simultaneous acquisition. However, an increment for simultaneous acquisition points has been suggested; for example, as a consequence of multichannel acquisition acoustic visualization through computerized interpolation has emerged being helpful to analyze lung sounds (LS) origin, distribution, and relation to ventilation. Nevertheless, quantitative analysis of lung sounds requires eliminating interference signals prior to the extraction of relevant features. The acquired signals not only contain LS but also heart sounds (HS) among other interferences. HS are unavoidable and sometimes represent severe disturbing interference. This paper proposes a HS cancellation scheme as an extension of a previous effort using the Empirical Mode Decomposition (EMD) and a combination of time warping with linear adaptive FIR filtering. Simulated signals are used to evaluate the performance of the proposed scheme under known and controlled scenarios.

I. INTRODUCTION

By a quantitative analysis of lung sounds (LS), several attempts have been made to avoid the subjectivity element of the pulmonary auscultation technique [1]. Collection of acoustic information on trachea and at several thoracic places has been done with one up to four microphones, but in a non-simultaneous fashion. Recently, different attempts have emerged where 16 or more microphones are used to acquire LS on the thoracic wall to study their temporal-spatial characteristics [2, 3]. Nevertheless, LS quantitative analysis has established the necessity to eliminate interference signals prior to the extraction of relevant features. Some researchers have tried to cancel heart sounds (HS) using different approaches where the interference sound is first localized and afterwards is cancelled [4, 5], others attempts try to reduce HS by direct estimation using Kalman filtering [6] and high–order statistics [7]. However, most of the efforts have been focused on processing real acquired signals under low or medium airflow and where the SNR for HS is favorable. Computational simulations are advised to evaluate the performance of a proposed methodology under known and controlled scenarios. This paper proposes a new scheme to first identify the position of each HS and afterwards reduce it. The scheme could be seen as an extension of a previous effort [4] by using a combination of Empirical Mode Decomposition (EMD), and a non-linear processing by a time-warping (TW) of the reference signal in the decomposition domain followed by a linear adaptive FIR filtering.

II. PROBLEM STATEMENT

It has been pointed out that LS and HS exhibit an overlapping of their frequency contents. For normal LS at the thoracic surface, the so-called vesicular sound, the frequency range seems to be up to 500 Hz [8] and for abnormal sounds like crackles sounds, the frequency range is up to 2000 Hz [8]. For normal HS acquired at the human chest, the frequency range is up to 200 Hz [9]. This overlapping precludes the use of deterministic filtering; consequently, adaptive filtering seems to be adequate for the task. However, the adapting filtering application called interference canceling requires the use of a reference signal that has to be statistically related to the interference one. The selection of the reference signal is not always easy.

In addition to the frequency overlapping factor, LS and HS show non-stationary behavior. The LS characteristics depend on the airflow while for HS, it has been established in their genesis valvular elements with constant frequencies, and a muscular element with changing frequencies like a chirp signal [9, 10]. Accordingly, processing techniques that deal with these non-stationary behaviors are necessary. As well, in a multichannel acquisition system, HS characteristics could change according to the acquisition position on the chest [11].

For a multichannel acquisition system, this paper proposes to achieve HS cancellation by processing acoustic information in a channel by channel basis localizing firstly HS position, and secondly, canceling each HS using a reference signal gotten from the same channel. In particular, for localizing HS, the authors propose to use empirical mode decomposition. EMD allows dealing with nonstationary and nonlinear signals corresponding to an automatic and adaptive time-varying filtering [12, 13]. EMD has been applied to biomedical signals for analysis of gastroesophageal information [14], and interference reduction in electrogastograms [15].

III. BACKGROUND

A. The empirical mode decomposition

The main idea behind EMD is to identify the intrinsic mode functions (IMF), the oscillatory modes of a signal by its time scales [5]. The signal s(t) is represented by:

$$s(t) = \sum_{k=1}^{N} \mathrm{IMF}_k(t) + r_N(t) \qquad (1)$$

where N is the number of IMFs, and $r_N(t)$ represents a residual signal. There are two conditions that IMFs must satisfy: (a) the number of extrema and the number of zero crossings must be equal or differ at most by one, in the whole data set and; (b) be symmetric with respect to local zero mean. The procedure to extract the IMFs can be reviewed in [12].

EMD is a complete, orthogonal, local and an adaptive decomposition [12]. An attractive feature of EMD in comparison with others analysis techniques is the adaptive feature, i.e., all the extracted information depends completely on the data, and its time scales, special kernels or waveforms are not needed. Conversely, wavelet analysis owns some limitations as being non-adaptive and with limited temporal resolution since the same basic wavelet is used for all the data.

B. Linear adaptive filtering and time-warping

An adaptive filter is a self-designing system that relies its operation on a recursive algorithm for determining its impulse response under a time-varying environment and when knowledge of the signal characteristic is not available [16]. Most of the adaptive filter applications include FIR filters due to its simplicity and stability but they have limitations when non-linear components are involved. The least mean squares (LMS), that minimizes the MSE between the primary input and the reference signal, is one of the most popular recursive algorithms to adapt the filters weights due to its simplicity and low computational requirements.

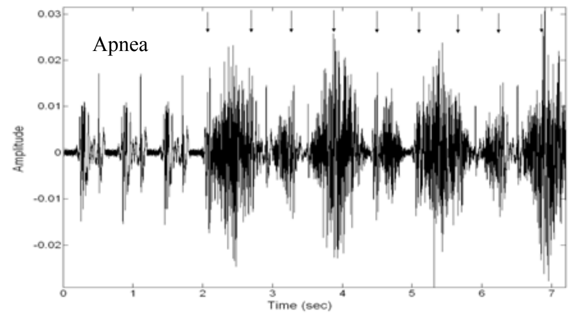
TW is a process that warps the time axes of one time series in such a way that corresponding samples of two time series appears at the same location on a common time axis, i.e., the procedure tries to time alignment two time series. TW is used in this paper to try to improve the elimination of the interference signal and overcome the problems involved in the reference selection and possible nonlinear changes in HS by the breathing process. TW is achieved here by piecewise linear stretching and compression of the information of the reference signal before being filtering by the linear adaptive FIR filter [17].

IV. METHODOLOGY

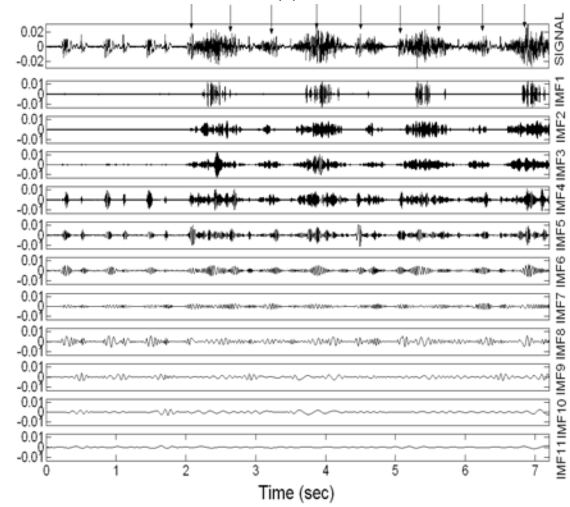
A. Simulated lung sound

The acquired LS was simulated following the mathematical expression:

$$z(n) = \sum_{i=1}^{M_1} s_1(n-\Delta_{1i}) + \sum_{i=1}^{M_2} s_2(n-\Delta_{2i}) + \sum_{i=1}^{M_1} s_1^{bs}(n-\Delta_{1i}^{bs}) + \sum_{i=1}^{4} v(n-\Delta_{bi}) + w(n) \qquad (2)$$



(a)



(b)

Figure 1. (a) Simulated LS signal and (b) the corresponding EMD.

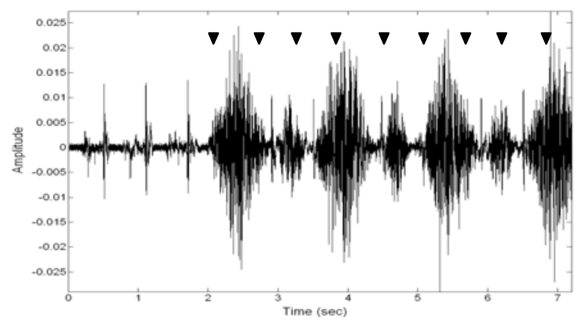


Figure 2. Filtered LS signal, the triangles point out time positions where the original s_1 was reduced.

where z(n) represents the acquired LS signal in one channel, s_1 and s_2 indicate first and second HS at different time positions Δ_{1i} and Δ_{2i}, simulating a cardiac frequency of 100 b/min. The sound s_1^{bs} corresponds to a first HS modified by the breathing process resulted from the convolution $s_1^{bs}(n) = h_{1ir}(n) * s_1(n)$, with $h_{1ir}(n)$ the impulse response of "unknown" systems representing the correlation between the reference and interference HS [4]. The HS were extracted from real HS files acquired at positions close to heart and during breath holding maneuver. The HS were acquired at 5 KHz using a subminiature electret microphone with an air plastic coupler. The HS were inserted considering different SNR as indicated in table I.

Regarding v(n), representing a normal breathing sound, this signal was simulated filtering a Gaussian noise sequence, covering the frequency range of real LS acquired on the human chest, and considering frequency overlapping with HS. Four v(n) signals were considered for simulation of inspiratory and expiratory phases at positions Δ_{bi}. Also, the simulated signal z(n) included an apnea section to select a reference signal for the cancellation scheme. Finally, w(n) is an additive noise.

B. The proposed processing scheme

The simulated LS signal z(n) was processed by EMD and the IMFs were obtained. Afterwards, according to a quasi-periodic behavior of the HS components in each IMF, a subset of IMFs was selected to remove HS from them. The correlation function was used to detect the temporal position of HS components in each IMFs using as a reference a HS component from the apnea phase.

A FIR adaptive filter, using the LMS algorithm, in an interference canceling application was used on each of the selected IMFs with and without applying first a TW to the signal. Afterwards, the processed and unprocessed IMFs were added to recover the filtered z(n) signal.

V. RESULT

Fig. 1(a) shows the simulated z(n) signal with three complete breathing cycles and where the HS in the apnea section are clearly visible. For s1, nine HS are inmersed in the breathing section at the positions pointed out by arrows with SNRs as shown in Table I. Fig. 1(b) shows z(n) at the top, with arrows pointing out the HS positions, and the eleven IMFs provided by the EMD. Fig. 2 shows the filtered version of z(n) without time-warping and an adaptive filter of order 12. In this case, the filtering was only achieved for the first HS, i.e., s_1. A similar procedure could be applied for s_2. Fig. 3(a) and 3(b) show the spectrograms for z(n) and filtered z(n) from time 0 to around 4.5 sec to see the differences between both signals. Table I shows the power, calculated via the spectrogram, of the estimated interference using or not using TW. The estimated s_1 is obtained adding all the selected IMFs that underwent the processing.

VI. DISCUSSION

As shown in fig. 1(b), eleven IMFs were obtained for z(n). By visual inspection, it seems that from IMF_1 to IMF_3, the three IMFs with the higher oscillatory behavior, contain mainly oscillatory information from LS.

On the other hand, from IMF_4 to IMF_{11} the oscillatory information belongs to both HS and LS, i.e., both sounds share time scales. In consequence, none IMFs could be just simply eliminated to reduce HS in the original signal domain. However, it is also clearly evident oscillatory information that is temporal concurrent with the known s_1 temporal positions. For example, in fig. 1(b) some of the coincident oscillatory information in IMF_5 is indicated by triangles. Taking advantage of the enhancement of HS oscillatory information in some IMFs, the correlation function was calculated for a subset of IMFs, from IMF_4 to IMF_{10}, using HS oscillatory information from the apnea phase. With the temporal positions provided by the correlation function, a reference signal was shaped for the adaptive filter but it could be previous processed or not by TW.

Fig. 2 shows the filtered z(n) where is possible to see that s_1 were significantly reduced at the apnea phase. For the rest of the filtered z(n) is more difficult to visually corroborate a reduction of s_1 yet for certain time positions is possible to observe the reduction, those positions are indicated by triangles in fig. 2. It seems that the processing did not modify the morphology of LS.

By visual comparison between fig. 3 (a) and 3 (b) is also possible to see the reduction of s_1 in the original z(n). However, there is a little modification of LS information after the procedure since Table I indicates that the power of the estimated interference s_1 to be subtracted from interference signal in primary signal in general shows more power at frequencies band of 300-600 Hz and 600-1500 Hz, even a little worst when the TW is included. This is due to the application of the adaptive filtering afterwards TW.

VII. CONCLUSIONS

The proposed methodology seems to be promising for HS reduction since even in adverse SNR for HS, it could provide an estimated interference sound with little modification of LS characteristics.

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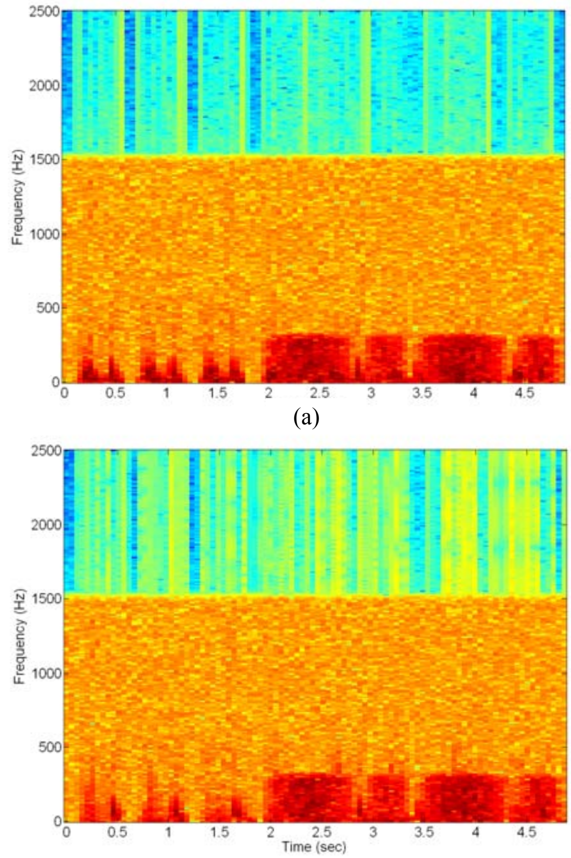

(a)

(b)

Figure 3. (a) Spectrogram of z(n) and (b) filtered z(n) for the time interval from 0 to 4.7 sec.

Table I. PSD Values for Inserted and Estimated S_1												
S_1 Position number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
SNR (dB)	56 (A)	54 (A)	55 (A)	13	1.3	4	-13	33	11	-6	10	-11
F. Band 0-300 Hz	**PSD**											
Inserted S_1	1066.9	1354.1	1126.4	838.1	929.2	598.4	935.3	811.2	912.7	588.0	923.4	811. 8
Estimated S_1 without TW	1034.7	1209.6	1149.5	982.8	1194.2	800.0	1364.8	885.1	1040.5	449.7	1125.2	1436.0
Estimated S_1 with TW	1036.6	1178.1	1100.6	1036.2	1207.0	808.1	1519.5	862.0	1067.1	437.0	1178.4	1474.0
F. Band 300-600 Hz	**PSD**											
Inserted S_1	40.8	53.0	47.5	35.8	36.6	26.7	40.1	34.6	38.8	26.8	40.9	36.6
Estimated S_1 without TW	22.1	24.1	22.4	33.8	52.6	47.1	67.8	36.6	38.2	21.6	41.0	89.0
Estimated S_1 with TW	21.6	41.8	33.2	67.0	120.0	100.1	216.0	50.2	53.3	50.0	94.0	156.5
F. Band 600-1500 Hz	**PSD**											
Inserted S_1	14.0	14.0	14.8	10.7	10.4	7.8	11.7	10.7	9.40	8.1	10.1	9.9
Estimated S_1 without TW	5.8	7.0	5.7	11.2	21.0	19.7	27.1	16.5	14.0	12.0	17.5	27.4
Estimated S_1 with TW	8.4	16.7	14.0	22.4	62.0	67.6	75.4	44.2	36.1	25.5	42.4	76.0

A: Apnea segment; F. Band: Frequency Band; TW: Time-warping