HEART SOUND LOCALIZATION AND REDUCTION IN TRACHEAL SOUNDS BY GABOR TIME-FREQUENCY MASKING

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Abstract: *Respiratory sounds, i.e. tracheal and lung sounds, have been of great interest due to their diagnostic values as well as the potential of their use in the estimation of the respiratory dynamics (mainly airflow). Thus the aim of the study is to present a new method to filter the heart sound interference from the tracheal sounds. Tracheal sounds and airflow signals were collected by using an accelerometer from 10 healthy subjects. Tracheal sounds were then pre-processed by Recursive Least Square - Adaptive Noise Cancellation (RLS-ANC) filter to remove background noise. Gabor time-frequency expansion was used for both heart sound localization and reduction problem. In the first step of filtering, RLS-ANC successfully filtered out the broad - band ambient noise. Reconstruction of tracheal sound was achieved from modified Gabor coefficients without heart sound noise. Visual inspection and quantitative analysis demonstrated that Gabor time-frequency masking with RLS-ANC filters provides successful tracheal sound signal separation.*
Keywords: *tracheal sound filtering, Gabor expansion, time-frequency filtering.*

1. Introduction

Respiratory sounds, i.e. tracheal and lung sounds have been of great interest due to their diagnostic values as well as their potential to be used in the estimation of the respiratory dynamics (mainly airflow) [1,2]. The first step to utilize the respiratory sounds is to remove any noise contaminating the valuable spectra-temporal bands of the signals, such that high energy heart sounds interfere with the low energy respiratory sounds at the low frequency band [2]. Heart sound interference should be removed from the respiratory sound signal completely and also efficiently, i.e. without losing or harming the respiratory sound signal overlapping with the heart sound effected frequency band. This is required due to two important factors:

i. Low energy band of the respiratory sound is proved to contain valuable diagnostic information [1],

ii. In order to benefit from respiratory sounds to estimate various respiratory parameters, mainly respiratory airflow and breathing frequency, it is required to work on the clean respiratory sound signal with distinguishable inspiration and expiration parts [2-4].

Statistical signal processing methods were proposed to filter out any noise in the respiratory sound signal, as well as, different approaches based on adaptive filtering [5-7] and time-frequency filtering [7,8] were applied to remove the heart sound noise without altering the respiratory sound signal. All these promising methods achieved a significant degree of success. However, although heart sounds were localized perfectly with these methods, filtering of the respiratory sound signal was still on debate. Moreover, implementations of these methods were not straight forward and needs careful computerization, thus not suitable for automated diagnosis systems.

The need for a fast and effective method can be overcome by the Gabor type time-frequency representation of the respiratory sounds. Gabor representation of a signal provides a convenient means to modify the signal in the time-frequency domain. By adjusting the magnitude of the Gabor coefficients in a prescribed manner and reconstruction of the modified signal using the inverse Gabor expansion, time-frequency filter is easily implemented. In our previous study [9], time-frequency masking technique based on Gabor expansion was applied successfully for the respiratory sound noise reduction problem. However, in [9] tracheal sound signal was used from database as a respiratory sound signal. Given the fact that tracheal sounds from database are pre-processed and cannot represent the real life situation, raw recorded data should be processed. However, raw respiratory signals include not only heart sound signals but also broad band ambient noise. Therefore, the goal of this paper is to evaluate the use of Recursive Least Square - Adaptive Noise Cancellation (RLS-ANC) filter to remove background noise and to assess the effectiveness of Gabor time-frequency masking techniques for heart sound noise localization and reduction problem. Transient noises such as speech and impulsive noise are out of scope of this study.

Received on: 16.01.2016
Accepted on: 21.03.2017

2. Materials and Methods

2.1. Discrete Gabor Expansion

The Gabor expansion and Gabor transform is the time domain - to - time-frequency domain linear and two sided transformation of the signals. By applying sampling theory to continues-time Gabor expansion, discrete Gabor expansion of a finite (or periodic) discrete-time sequence with length L can be defined as [10]:

$$f(k)=\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}c_{m,n}g_{m,n}(k),\ k=0,\cdots L-1 \tag{1}$$

where synthesis function $g_{m,n}(k)$ is the $m\Delta M$ time shifted and $n\Delta N$ frequency modulated version of the Gabor window function $g(k)$ also called logons or atoms:

$$g_{m,n}(k)=g(k-m\Delta M)e^{\frac{j2\pi n\Delta Nk}{L}} \tag{2}$$

In Eq (2) ΔM and ΔN are time and frequency sampling intervals, respectively. M and N are the number of sampling points in time and frequency domains ($\Delta MM=\Delta NN=L$). Ideally, $g(k)$ should be well localized in both time and frequency (i.e., should decay rapidly outside a small region in the time-frequency space), in which case the coefficients $c_{m,n}$ give good indications of the content of the signal at time $m\Delta M$ and frequency $n\Delta N$. Originally, the synthesis function was chosen by Gabor as a Gaussian window, because it maximizes the concentration in the time-frequency plane

The existence of (1) has been found to be possible for arbitrary $f(k)$ only for $\Delta M\Delta N\leq L$ (or $MN\geq L$). This is called the oversampled case and the synthesis functions are no longer linearly independent. At the critical sampling case $\Delta MM=\Delta NN=L$, the logons are linearly independent, but are not orthogonal in general (Balian-Low obstruction) [10,11]. This means that the Gabor coefficients $c_{m,n}$ are not simply the projections of $f(k)$ onto the corresponding logons $g(k)$ (i.e. the analysis and synthesis windows cannot be the same).

According to [12] Gabor coefficient $c_{m,n}$ is computed by the inner product rule for projecting $f(k)$ onto $\gamma(k)$, auxiliary function, or bi-orthogonal window, i.e.,

$$c_{m,n}=\sum_{k=0}^{L-1}f(k)\gamma_{m,n}^{*}(k) \tag{3}$$

where again analysis function $\gamma_{m,n}(k)$ is the $m\Delta M$ time shifted and $n\Delta N$ frequency modulated version of the Gabor window function $\gamma(k)$:

$$\gamma_{m,n}(k)=\gamma(k-m\Delta M)e^{\frac{j2\pi n\Delta Nk}{L}} \tag{4}$$

Analysis function $\gamma(k)$, is also called dual window function of the synthesis window function since they can be interchangeable. If the windows $g(k)$ and $\gamma(k)$ are chosen biorthonormal, transform is called an orthogonal-like Gabor transform [10] and they validate the biorthonormal condition

$$\sum_{k=0}^{L-1}g(k+mN)e^{-\frac{j2\pi nMk}{L}}\gamma^{*}(k)=\delta(m)\delta(n) \tag{5}$$

where $0\leq m\leq\Delta N-1$ and $0\leq n\leq\Delta M-1$. Then the analysis formula given by Eq (3) allows the computation of the Gabor coefficients and the synthesis formula in Eq (1) the reconstruction of the signal $f(k)$. Zak transform can be used to compute the biorthonormal window $\gamma(k)$ associated to a given synthesis window $g(k)$. From an implementation point of view, this solution is not fully satisfactory since the computation of the biorthonormal window $\gamma(k)$ is numerically unstable. So in general, some degree of oversampling is considered, which introduces redundancy in the coefficients, in order to "smooth" the biorthonormal window $\gamma(k)$, for the sake of numerical stability. These considerations are closely connected to the theory of frames [13].

2.1.1 Computation of discrete orthogonal-like Gabor expansion

Eq.(1) and Eq. (3) can be expressed in the matrix form respectively as

$$\mathbf{f}=\mathbf{Gc} \tag{6}$$

$$\mathbf{c}=\mathbf{fW}^{*} \tag{7}$$

where the sequence **f** is expressed in the form of a column vector:

$$\mathbf{f}=\left[f_0\ f_1\cdots f_{L-1}\right]^T \tag{8}$$

G denotes the $L\times MN$ Gabor synthesis matrix having $g_{m,n}$ as its $(m+nM)$-th column, such that

$$\mathbf{G}=\begin{bmatrix} g_{0,0}(0) & \cdots & g_{M-1,N-1}(0)\\ \vdots & \ddots & \vdots\\ g_{0,0}(L-1) & \cdots & g_{M-1,N-1}(L-1)\end{bmatrix} \tag{9}$$

The Gabor expansion coefficients $c_{m,n}$ are written in the form of a column vector **c** of length MN:

$$\mathbf{c}=\left[c_{0,0}\ \ \cdots\ \ c_{M-1,N-1}\right]^T \tag{10}$$

$\mathbf{W}^{*}$ is the complex conjugate of $L\times MN$ analysis matrix constructed as same as **G**

Eq.(5) can also be expressed matrix-vector notation as:

$$\mathbf{HW}^{*}=\mathbf{I} \tag{11}$$

where **I** is identity matrix and **H** is a $MN \times L$ matrix constructed by [14]:

$$H\left(m\Delta M+n,k\right)=g\left(k+mN\right)e^{-\frac{j2\pi nMk}{L}} \quad (12)$$

where $0 \leq m \leq \Delta N - 1$ and $0 \leq n \leq \Delta M - 1$.

As it is explained earlier, in the oversampling case, linear system given Eq.(5) is underdetermined and solution that making the shape of $\gamma(k)$ and $g(k)$ as close as possible in the least square sense can be found [10]:

$$\Gamma=\min\sum_{k=0}^{L-1}\left(\frac{g\left(k\right)}{\left\|g\left(k\right)\right\|}-\frac{\gamma\left(k\right)}{\left\|\gamma\left(k\right)\right\|}\right)^{2} \quad (13)$$

This solution is then equated to the solution of the system Eq.(10) via pseudo-inverse method, i.e., the window satisfying Eq.(10) with minimal norm is given by:

$$\mathbf{W}^{*}=\mathbf{H}^{*}\left(\mathbf{H}\mathbf{H}^{*}\right)^{-1}\mu \quad (14)$$

Eq.(14) says that regarding to the oversampling case, biorthogal analysis window function can be easily obtained once the synthesis function is set. Other conclusion can be drawn as the similarity between the pair of dual functions $\gamma(k)$ and $g(k)$ is directly proportional to the oversampling rate.

2.1.2 Denoising by Gabor expansion

Gabor expansion can be used as a tool for a noise reduction, if either the noise components of the signal is well localized and occupies certain number of cells in time-frequency plane [15] or can be assumed that an independently identically distributed Gaussian noise [16]. Acquired respiratory sound signal is composed of many types of noise signals that needed to be filtered off. Heart sound signal can be considered as a periodic type noise signal since its location can be detected easily by any of linear time-frequency signal representations. However, a noise from an electronic measurement circuitry is usually Gaussian type white noise.

Regardless of the type of the noise included in the signal, Gabor coefficients thresholding or modification can be methods used for the noise reduction. Depending on the noise level and statistical properties of the noise, different algorithms are constructed for different tresholding levels [15-17]. In [16] the denoising algorithm was presented in the case of Gaussian type of the noise signal, whereas in [15] time-frequency domain denoising methods were utilized.

Gabor coefficients masking as denoising approach has a fairly simple algorithm. However, the care, that the analysis and synthesis window should be as close as possible, should be taken. Once the constraint of Eq.(11) is satisfied, it is easy to show that the modified Gabor coefficients are closer to the Gabor coefficient of the modified signal via transform Eq.(7) (Proof is in [15]).

2.2. Gabor Representation of the Tracheal Sound

2.2.1 Data Acquisition and preprocessing

In this work respiratory sounds were acquired from 10 healthy subjects in ranging age of 20 to 30 year-old. Respiratory sounds were recorded by 2 accelerometers (PCB 353B16) placed over suprasternal notch and 3rd intercostal space posteriorly on the left. Respiratory air flow was measured by a pneumotachograph (Hans Rudolph RSS 100 0-160 L/min) attached on a facemask (Respironics Spectrum medium size). Subjects were instructed to breathe quietly without making extra effort. The low-noise operational amplifier was used with the gain factor of 5000 for amplification of the raw sound signals. Preprocessing also included RC band pass filter with the bandwidth of 7.5 Hz. to 2500 Hz. The signals were then digitized by data acquisition board (NI PCI-6221 M 16-bits). The sampling rate was 10 kHz. Acquired signals were displayed and saved for processing by data acquisition software (NI LabVIEW full development system).

2.2.2 Ambient noise filtering by RLS-ANC Adaptive Filter

Acquired data did not only contain heart sound and respiratory sound signals but also were affected by the ambient noise and the noise from electronic components. It has been proved that ordinary band pass filters were not useful in terms of noise reduction in the respiratory sound [1, 5, 8]. Thus Recursive Least Squares Adaptive Noise Cancellation (RLC-ANC) was used to filter out the ambient noise in the respiratory sounds.

The standard RLS adaptive filtering scheme consists of a finite-duration impulse response transversal filter and RLS algorithm, which upgrades the tap weights w_k of the transversal filter in a recursive manner so that the cost function is minimized [18]. The details of the RLS-ANC algorithm can be found in [9]. As a reference noise signal, the unconnected accelerometer output was recorded. As the RLS adaptive filter is highly sensitive to numerical instability [18], the filter order severely affects the performance of the filter. In order to keep computational time as low as possible, RLS-ANC filter order was chosen to be 8 on trial and error basis and the changes occurred at the spectrogram of the signals were observed. λ was set to 1 to be infinite memory.

2.2.3 Gabor analysis of respiratory sounds

After adaptive filtering, acquired tracheal sound signal includes both desired tracheal sound signal and heart sound noise. In this work, we used the generalized Gabor expansion for the respiratory sound signal modeling. For finite discrete-time signals, Gabor synthesis and analysis equations are given in Eq.(6) and Eq.(7).

For the synthesis function $g(k)$, we chose Gaussian type window in order to obtain well localized windows [11]. Below normalized Gaussian function is used:

$$g(k)=\left(\frac{\sqrt{2}}{\sigma}\right)^{1/2} e^{-\pi\left(\frac{k}{\sigma}\right)^2}, \quad 0 \le k < L \tag{15}$$

where L is the number of the data samples and σ is the standard deviation of the Gauss function

Selecting the standard deviation highly depends on the wavelength and the line of sight of the signal to be detected. By increasing the wideness, the Gabor expansion emphasizes lower frequencies, whereas higher frequencies of the sound signals can be detected with narrow Gabor expansion windows. Therefore in order to detect low frequency content of the respiratory sound signal we tried relatively high values of σ and 256 point of the window length was found optimum on the heart sound signal frequency band.

Biorthogonal sequence was computed using algorithms explained in section 2.1. Both the window and the biothogonal sequence are illustrated in Figure 1. $L = 10000$ sample segment was used to compute Gabor coefficients and we considered oversampling case with $M = 1000$ and $N = 10000$. The over sampling rate can be calculated as $r = \frac{M\times N}{L} = 1000$. Therefore, due to such a high oversampling rate and pursuing orthogonal-like Gabor transform, both of the window functions are Gaussian type with different amplitudes. Once biothogonal $\gamma(k)$ is determined by Eq.(14) and Eq (15), it is trivial to compute $c_{m,n}$ by Eq.(7).

4. Results

Figure 2 shows the spectrogram of the typical recorded tracheal sound signal from one of the representative subject before ambient noise filtering and the same signal after RLS-ANC adaptive filter. Power spectral density (PSD) plots of the signals are shown in Figure 3. Since, our criterion of successful filtering was to have less coloured spectrogram, as it is shown in Figure 2, the spectrogram of the RLS-ANC filtered sound signal has less noise artefacts. Moreover, heart sound noise components are clearer in the RLS-ANC filtered signal than in the original sound signal. Thus filtering off the background noise attenuates the broad-band noise component of the sound signals while

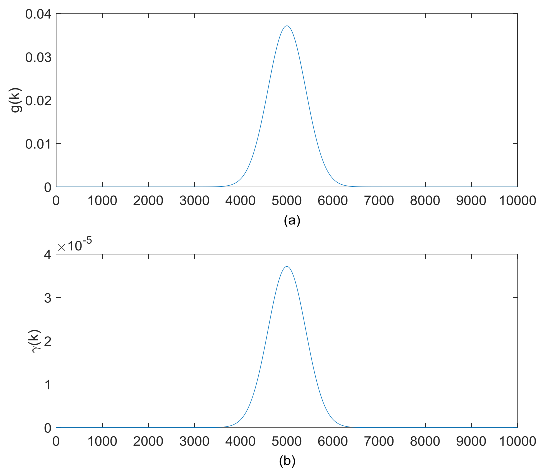

Figure 1. (a) Normalized Gaussian window, $g(k)$ and (b) optimum biorthogonal window, $\gamma(k)$.

exposing more readily sound spectral content. Figure 3 shows the decrease of the PSD in the whole frequency band of the tracheal sounds after the filtering.

Broad-band noise elimination with adaptive filtering was very successful because the ambient noise was uncorrelated with sound signals and cannot be locally identified. However, this is not the case for heart sound signal. Heart sound signal can only be eliminated by the time-frequency representation of the respiratory sound signal. Thus our second approach to the denoising problem was to express the sound signals with linear time-frequency transform.

Figure 4 shows the magnitude values of the Gabor coefficients, $c_{m,n}$ of typical tracheal sound signal in a contour plot before and after denoising. Note that only the positive half of the frequency axis is shown. In Figure 4a, we see that Gabor coefficients are visible only at the frequencies where high energy heart sound signals are present. In other words, most of the Gabor coefficients are close to zero outside the noisy region in the joint time-frequency domain of the tracheal sound signal. This can be explained with two important facts. First, with the selection of the Gaussian window length the low frequency band of the respiratory sound signal is emphasized, and second higher intensities of heart sound made the Gabor coefficient matrix sparse. In other words, coefficients related to heart sound component is too high, so that respiration related coefficients are regarded as zero. This is based on the calculations of the Gabor coefficients, as discussed in section 2.1. Thus, the desired signal can be obtained from the noisy signal by masking the high amplitude Gabor coefficients.

Figure 4b shows Gabor coefficients of the same signal segment after Gabor coefficient masking. As explained in section 2.1.2, applied masking technique is called soft clipping and used when the Gabor coefficients are sparse [16]. Heart sound reduction can be seen easily in both Figure 4 and Figure 5, which shows the PSD of the signals before and after Gabor denoising. It can be observed that only high power heart sound components were affected

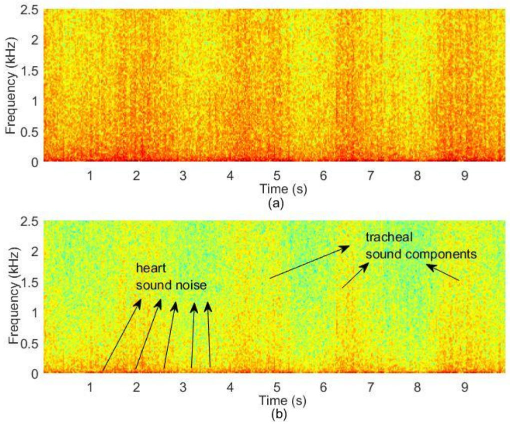

Figure 2. Typical representations of (a) raw recorded tracheal sound signal spectrogram, and (b) the spectrogram of the same signal after RLS-ANC adaptive filtering.

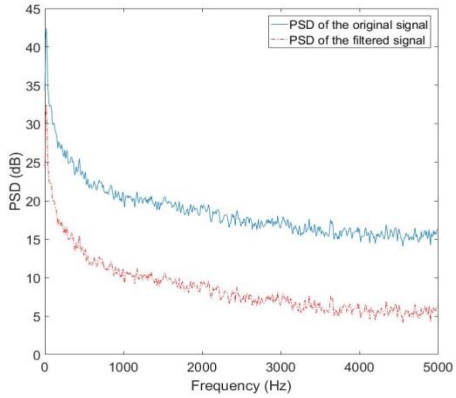

Figure 3. PSD comparisons of the tracheal sound signals before and after RLS-ANC filtering. (Solid line represents PSD of the original signal; broken line represents PSD of the broad band noise filtered signal).

from the denoising procedure, leaving other parts untouched. Figure 5 also includes the magnified low frequency part of the PSD, which emphasised that the tracheal sound signal was considerably decreased at the frequencies up to 150 Hz. This clearly demonstrates the effectiveness of the masking technique.

5. Conclusions

We removed the background noise and heart sound noise in the tracheal sound signal successfully by RLS-ANC adaptive filtering, generalized biorthogonal Gabor expansion and Gabor coefficient masking method. Both heart sound signal localization and filtering were done by the Gabor expansion. The noise filtering in the biomedical signals by Gabor expansion was done in the previous studies [19]. Here we applied the Gabor expansion to tracheal sound filtering problem and achieved the noise-free traceal sound signal at the end. It is proved that the respiratory sound signal is very well modelled by Gabor coefficients. Although the respiratory sound as a time-varying signal covers very large area in the time-frequency domain, the heart sound as a noise signal has very distinctive location and can be easily processed by the Gabor expansion. The linearity of the Gabor expansion suggests the possibility of further processing of the respiratory sound signals. For instance, one may consider the cross spectral analysis between the tracheal sound signal and the lung sound signal. Furthermore, similar analysis can be carried out by the selection of the windows for the adventitious sound spectrum. Finally, comparing to our previous study [20], although the figures shows the similar results, in terms of the computational cost and simulation duration Gabor expansion technique is more superior than the spectrogram and adaptive filtering technique.

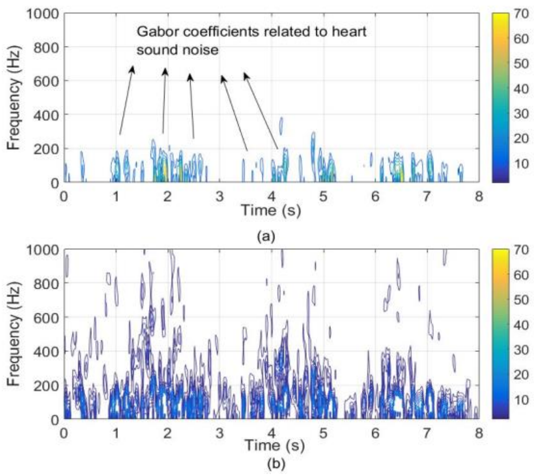

Figure 4. Typical representations of Gabor coefficients (magnitudes) for (a) the tracheal sound segment after RLS-ANC filtering and (b) same segment after soft clipping (denoising).

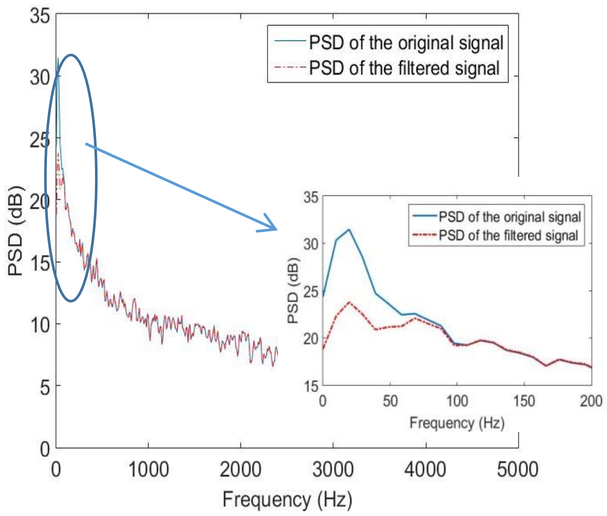

Figure 5. PSD comparisons of the tracheal sound signals before and after Gabor denoising. (Solid line represents PSD of the tracheal sound signal after RLS-ANC filtering, broken line represents PSD of the tracheal sound signal after Gabor denoising). Inserted subfigure is the magnified region between $0 - 200\ Hz$.

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