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Time-shared channel identification for adaptive noise cancellation in breath sound extraction

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Abstract: Noise artifacts are one of the key obstacles in applying continuous monitoring and computer-assisted analysis of lung sounds. Traditional adaptive noise cancellation (ANC) methodologies work reasonably well when signal and noise are stationary and independent. Clinical lung sound auscultation encounters an acoustic environment in which breath sounds are not stationary and often correlate with noise. Consequently, capability of ANC becomes significantly compromised. This paper introduces a new methodology for extracting authentic lung sounds from noise-corrupted measurements. Unlike traditional noise cancellation methods that rely on either frequency band separation or signal/noise independence to achieve noise reduction, this methodology combines the traditional noise canceling methods with the unique feature of time-split stages in breathing sounds. By employing a multi-sensor system, the method first employs a high-pass filter to eliminate the off-band noise, and then performs time-shared blind identification and noise cancellation with recursion from breathing cycle to cycle. Since no frequency separation or signal/noise independence is required, this method potentially has a robust and reliable capability of noise reduction, complementing the traditional methods.

Keywords: Lung sound analysis; Noise cancellation; Blind signal extraction; System identification; Adaptive filtering

1 Introduction

Continuous monitoring of lung sounds is of essential importance in the medical diagnosis for patients with lung diseases and in the detection of critical conditions in operating rooms. To obtain quantitative and reliable diagnosis and detection, it is critically important that respiratory auscultation retain sounds of high clarity. Clinical acoustic environment poses great challenges for lung sound acquisition. Unlike acoustic labs in which noise levels can be artificially controlled and reduced, and lung sounds can be processed off-line, operating rooms are very noisy due to surgical devices, ventilation machines, conversations, alarms, etc. The unpredictable and broadband natures of such noises provide operating rooms with a very difficult acoustic environment. Since the lung sound cannot be directly controlled and noises come from many sources and cannot be measured at source, separating lung sounds from noises is a blind source extraction problem.

Techniques for canceling noises that are off signal bands (frequency separation) or independent of signals (statistical separation) are quite effective. The former can be attenuated by designing appropriate band-pass filters, and the latter by adaptive noise cancellation (ANC). However, in practice, when noises overlap with the lung sound signal frequency band, direct filtering can no longer eliminate the noises. Also, when noises correlate with lung sounds, they introduce a fundamental identification bias on the channel model that cannot be easily removed. Consequently, this model bias causes quality decrease of noise cancellation, rendering traditional adaptive noise canceling techniques ineffective.

In this paper, we introduce a new noise reduction methodology that is uniquely designed to reduce the effect of signal/noise correlation. This method is derived on the basis of the unique nature of breathing sounds: 1) Breathing sounds are not stationary, and usually have three stages (inhale, exhale, and transitional pause). 2) Sounds in inhale and exhale stages contain rich information about lung functions and can be processed for diagnosis. 3) During

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transitional pause, lung sounds are very low and noises are dominant. Our noise canceling approach combines this unique method with the regular filtering technique. We first use a high-pass filter to eliminate the off-band noises (for example, sensors rubbing with skin or chest movement, etc.). After-filtering signals are then used in conducting blind channel identification during pause interval in breathing cycles, and noise cancellation during inhale and exhale. Upon establishing a reliable model of noise transmission channels, noise cancellation can be achieved even when signal and noise are highly correlated during inhale and exhale.

Our sound acquisition system consists of several lung sound sensors (that can be special microphones, electronic stethoscopes, or small accelerometers) on auscultation sites such as tracheal and bronchial, and one or more noise reference sensors. Sound waves acquired by the sensors will then be processed. In order to obtain noise measurements that represent the lumped impact of distributed and multi-source noises on the lung sensors, noise reference sensors are placed in vicinity of the lung sound sensors. Sound waves acquired by the sensors are fed into an analog/digital data acquisition module, manufactured by the National Instrument, Inc., for signal input, scaling, samqling rate synchronization, and other signal conditioning. Lung-sound signals and noise reference are then inputted to the following consecutive modules: a high-pass filter module, a noise cancellation module, a pattern recognition and diagnosis module, and a display module. The main blocks of the system are depicted in Fig. 1.

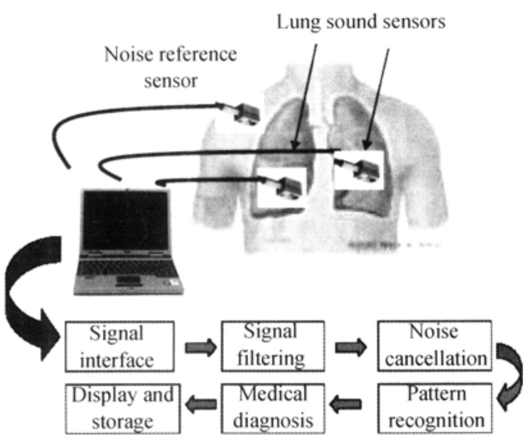


Fig. 1 A multi-sensor lung sound processing system.

This paper establishes the essential theoretical foundation of this methodology, while using both simulated and real data of breathing sounds to validate its efficacy. To understand the fundamental impact of signal/noise correlation on quality of channel identification, we first derive convergence and convergence rates of the traditional ANC in Section 3. The impact of signal/noise correlation is analyzed in Section 4. We show that correlation introduces identification bias and reduces convergence rates, by using large deviations principles. The main idea of the time-shared channel identification and noise cancellation is explained in Section 5. The basic cycle-to-cycle iteration algorithm is introduced. To validate the utility of this method, several typical cases of medical diagnosis applications are employed. Improvement of decision and diagnosis accuracy due to noise reduction is discussed.

The problems of blind separation or blind extraction of source signals from noisy environment have received wide attention in various fields such as biomedical signal analysis and processing, geographical data processing, speech and image recognition and wireless communications [1 ~ 8]. Although their underlying principles and approaches are different, many of the techniques are based on the classic principles of adaptive noise canceling. The ANC approach usually reduces the noise based on reference signals, which give information about the noise interference acting on the observed data [9,10]. Since ANC does not require frequency-band separation as most classical frequency filtering methods rely on, it provides an efficient noise cancellation method when signal/noise have overlapping frequency bands but independent statistically. In other words, it is efficient in canceling the in-band noise, which would be impossible to obtain by using direct noise filtering. However, the basis of the ANC method is on the constraint that the noise signals be statistically independent with the source signals. In practice, this condition may not be satisfied. The method introduced in this paper complements the traditional filtering and ANC for applications in which time-varying statistical features allow us to perform channel identification more accurately than ANC, leading to significantly improved quality of noise cancellation.

The key ideas of this paper were first reported in [11,12]. They were further detailed with experimental results in [13]. Some related identification algorithms with applications to anesthesia monitoring were discussed in [14].

2 Adaptive noise cancellation in lung sound monitoring

2.1 Off-band noise filtering

Consider the sensor system shown in Fig. 1. The noise reference sensor, which is placed in vicinity to the lung sensors, receives most environment noises from all the sources, just like the lung sensors, but does not receive many lung sounds. It was noticed that when sensors are placed on skin, they may produce some skin-scraping noises that vary from sensor to sensor. Also, lung sensors may catch some chest movement noises while reference sensors may not. These phenomena make the noise reference sensor incapable of representing noises received by the lung sensors. Fortunately, these noises are usually in a low frequency band off lung sounds and can be eliminated with regular filtering. As a result, we use a high-pass filter to remove the off-band noise before the noise canceling module. After this step, the noise reference can be readily used in channel identification and noise cancellation modules.

2.2 Virtual noise configuration

The location proximity between the lung and reference sensors allows us to represent noises from many sources approximately by a lumped noise near the reference sensor, such as d in Fig.2.

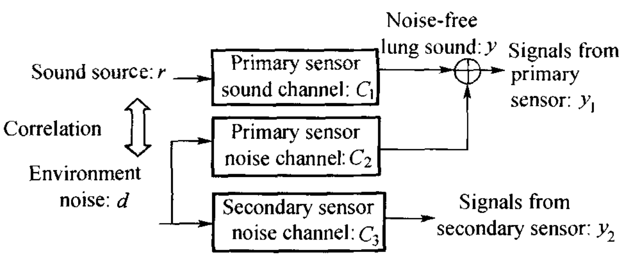


Fig.2 Sound channels.

If we view the measurement y_2 from the reference sensor as a virtual noise source, we basically replace distributed noise sources d (which are impossible to describe accurately and separately) in a lumped noise source y_2, as shown in Fig.3. The problem of noise cancellation is now reduced to identification of the virtual noise channel G (in terms of the system in Fig.2, G is the inverse of C_3 followed by C_2). Indeed, if we can estimate the noise channel G, then the noise-free lung sound y can be approximately extracted as

$$\hat{y} = y_1 - \hat{G}y_2.$$

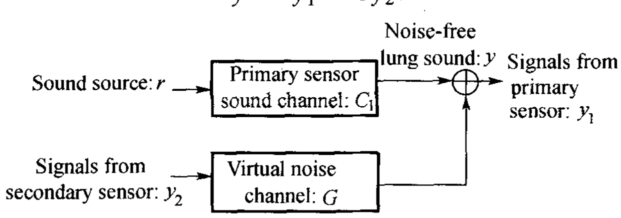


Fig. 3 Virtual noise formulation.

2.3 Channel identification and adaptive noise cancellation

For identification of G, the system $y_1 = y + Gy_2$ can be viewed as an input-output system $x = Gu + d$ in which $x = y_1$ is the output, $u = y_2$ is the input, and $d = y$ is a disturbance (although it is actually the useful signal we are seeking). Since G is stable, it can be modeled by its impulse response $g = \{g_0, g_1, \cdots\}$. Consequently, the above input/output relationship can be represented in a regression

$$x_k = \varphi_k^{\mathrm{T}}\theta + \tilde{\phi}_k^{\mathrm{T}}\tilde{\theta} + d_k,$$

where $\phi_k^{\mathrm{T}} = [u_k, \cdots, u_{k-n+1}]$ is the principal regression vector, $\theta = [g_0, \cdots, g_{n-1}]^{\mathrm{T}}$ is the parameter vector of the modeled part of G, $\tilde{\phi}_k^{\mathrm{T}} = [u_{k-n}, \cdots]$ and $\tilde{\theta} = [g_n, \cdots]$ represent unmodeled dynamics. In this paper, we will concentrate on the uncertainty from noises. The issue of unmodeled dynamics and its impact on identification accuracy was discussed in detail in [15].

The standard adaptive noise cancellation is based on the following basic procedures.

1) Identification: The standard least-squares estimation leads to an estimate of the parameter θ of G, on the basis of N data points, as

$$\hat{\theta}_N = \Big(\frac{1}{N}\sum_{k=1}^{N}\phi_k\phi_k^{\mathrm{T}}\Big)^{-1}\frac{1}{N}\sum_{k=1}^{N}\phi_k x_k,$$

when $\frac{1}{N}\sum_{k=1}^{N}\phi_k\phi_k^{\mathrm{T}}$ is non-singular. The corresponding estimation error is

$$e_N = \Big(\frac{1}{N}\sum_{k=1}^{N}\phi_k\phi_k^{\mathrm{T}}\Big)^{-1}\Big[\frac{1}{N}\sum_{k=1}^{N}\phi_k\tilde{\phi}_k^{\mathrm{T}}\tilde{\theta} + \frac{1}{N}\sum_{k=1}^{N}\phi_k d_k\Big].$$

2) Noise Cancellation: The reconstructed signal $\hat{d}_N$ at time N will be

$$\hat{d}_N = x_N - \phi_N^{\mathrm{T}}\hat{\theta}_N.$$

This process can be easily recursified to reduce computational burden at each time instant, leading to a recursive least-squares algorithm:

$$\begin{aligned} K_N &= \frac{P_{N-1}\phi_{N-1}}{1 + \phi_{N-1}^{\mathrm{T}}P_{N-1}\phi_{N-1}}, \\ P_N &= (I - K_{N-1}\phi_{N-1}^{\mathrm{T}})P_{N-1}, \\ \hat{\theta}_N &= \hat{\theta}_{N-1} + K_N(y_N - \phi_N^{\mathrm{T}}\hat{\theta}_{N-1}). \end{aligned} \tag{1}$$

2.4 Convergence of ANC

Assume that the underlying probability space is $\{\Omega, F, P\}$. ANC works well under certain conditions as discussed below. Consider the following terms in the estimation errors:

$$p_N = \frac{1}{N}\sum_{k=1}^{N}\phi_k\phi_k^{\mathrm{T}},$$

$$q_N = \frac{1}{N}\sum_{k=1}^{N}\phi_k\tilde{\phi}_k^{\mathrm{T}}\tilde{\theta},$$

$$r_N = \frac{1}{N}\sum_{k=1}^{N}\phi_k d_k.$$

Typically, the following assumptions are made on u_k and d_k in ANC.

Assumption A1 1) No unmodeled dynamics, that is, $\tilde{\theta} = 0$. This requires a complex model structure to capture all channel dynamics.

2) $\{u_k\}$ is a stationary ergodic sequence satisfying $Eu_k = 0$. u_k is bounded by β uniformly in k and in $\omega \in \Omega$.

3) $\sum_{k=1}^{N}\phi_k\phi_k^{\mathrm{T}}/N$ is nonsingular for any $N \geqslant n+1$ with probability one (w.p.1).

4) $\{d_k\}$ is a sequence of i.i.d. random variables with $Ed_k = 0, Ed_k^2 = \sigma^2 > 0$, and $\{d_k\}$ is independent of $\{u_k\}$.

Under Assumption A1, ANC provides appealing properties as indicated in Theorem 1.

Theorem 1 Under Assumption A1, with probability one(w.p.1), as $N \to \infty$

$$\begin{cases} \frac{1}{N}\sum_{k=1}^{N}\phi_k\phi_k^{\mathrm{T}} \to M, \\ \left(\frac{1}{N}\sum_{k=1}^{N}\phi_k\phi_k^{\mathrm{T}}\right)^{-1} \to M^{-1}, \\ r_N = \frac{1}{N}\sum_{k=1}^{N}\phi_k d_k \to 0, \end{cases} \tag{2}$$

where M and M^{-1} are positive definite.

Proof Since $\{u_k\}$ is stationary and mixing, [16, Remark 5.3, p.488] implies that it is strongly ergodic. By virtue of [16, Part (f) of Theorem 5.6, p.487], the strong ergodicity, in turn, yields that for any function $h(\cdot)$,

$$\frac{1}{N}\sum_{k=1}^{N}h(u_k, u_{k+1}, \cdots) \to Eh(u_1, u_2, \cdots) \text{ w.p.1}. \tag{3}$$

Thus (3) together with the Crámer-Wold device [17, p.48] leads to

$$\lim_{N\to\infty}\frac{1}{N}\sum_{k=1}^{N}\phi_k\phi_k^{\mathrm{T}} = M \text{ w.p.1},$$

and the limit M is positive definite owing to A1. Thus we also have

$$\left(\frac{1}{N}\sum_{k=1}^{N}\phi_k\phi_k^{\mathrm{T}}\right)^{-1} = M^{-1} \text{ w.p.1},$$

and M^{-1} is positive definite.

By the independence of $\{u_k\}$ and $\{d_k\}$, $E[\phi_k d_k \mid F_{k-1}] = 0$, so $\{\phi_k d_k\}$ is a martingale difference sequence with respect to the σ-algebra $F_k = \{u_j, d_j : j \leqslant k\}$. Moreover,

$$\sum_{k=1}^{\infty}\frac{1}{k^2}E\|\phi_k d_k\|^2 = \sum_{k=1}^{\infty}\frac{1}{k^2}E[\phi_k^{\mathrm{T}}\phi_k]E[d_k^2] < \infty.$$

By virtue of [18, Theorem 2.20], $\sum_{K=1}^{N}\phi_k d_k/N \to 0$ w.p.1. □

Despite these appealing features, ANC encounters significant challenges when the signal and noise are not independent or the underlying processes are not stationary. We will explore these issues in the next section.

3 Signal/noise correlation and quality of channel identification

3.1 Correlation and accuracy of channel estimation

Assumption A1, however, is often violated in this application. First, for channel identification, breathing sounds are viewed as noises. It is easily understood by observing typical waveforms of breathing sounds that they are not stationary. Fig.4 is a typical respiratory sound. For signal processing, a ventilation or breathing cycle is divided into three stages (see Fig.4): Inhale (T_i), exhale (T_e), and transitional pause ($T - T_i - T_e$). They are identified 1) by ventilator variables, e.g., airway pressure cycles (positive-negative-neutral) in ventilated patients; or 2) by smoothed breathing wave profiles in natural breath. Apparently the power during inhale is much larger than that in the pause phase. Accordingly, for signal processing, lung sounds may be considered as consisting of three stochastic processes: Inhale, exhale, pause. Each will have different properties and they are interlaced by switching from one

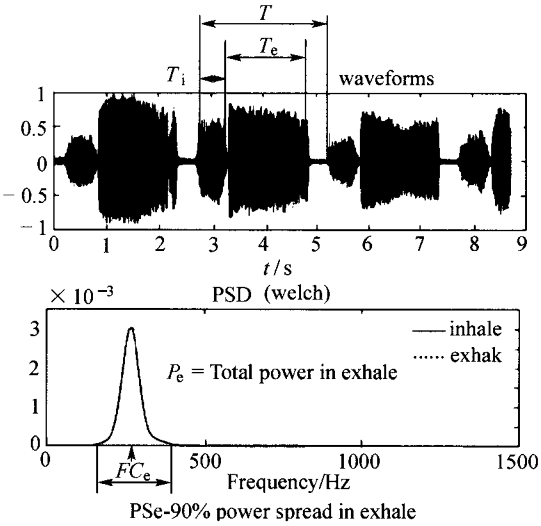


Fig. 4 Main lung sound characteristics.

process to another during a breath cycle, repeatedly from cycle to cycle. This formulation is consistent with the utility of lung sounds in diagnosis, and is essential in our methodology development. This formulation will be further detailed later.

Secondly, the independence between u_k and d_k is not always a valid assumption (there are at present no established results that verify sound/noise independence in this application). When u_k and d_k are statistically correlated, accuracy of channel identification under ANC will be significantly compromised. To understand the impact of signal/noise correlation on estimation accuracy, hence quality of noise cancellation, we will investigate behavior of the estimates when u_k and d_k are correlated.

Consider a simplified system (without unmodeled dynamics)

$$x_k = \phi_k^{\mathrm{T}} \theta + d_k.$$

Assume that u_k and d_k are stationary, zero mean, and are uniformly bounded (this is merely for simplicity of analysis so that all the moments of these signals exist). Define $r_m = Eu_k u_{k+m}$ (auto-correlations of u_k) and $c_m = Eu_k d_{k+m}$ (correlations between u_k and d_k). Let

$$R_u = \begin{bmatrix} r_0 & r_1 & \cdots & r_{n-1} \\ r_1 & r_0 & \cdots & r_{n-2} \\ \vdots & \vdots & \cdots & \vdots \\ r_{n-1} & r_{n-2} & \cdots & r_0 \end{bmatrix}, \; B = \begin{bmatrix} c_0 \\ c_1 \\ \vdots \\ c_{n-1} \end{bmatrix}. \quad (4)$$

Assumption A2 Assume Assumption A1 with 2) and 4) replaced by: The pair of processes $\{u_k, d_k\}$ is stationary and ergodic such that u_k is bounded by β uniformly in k and in $\omega \in \Omega$ and $Eu_k = 0$, that $Ed_k = 0, Ed_k^2 = \sigma^2 > 0$.

Theorem 2 Under Assumption A2, with probability one(w.p.1), as $N \to \infty$.

$$\begin{cases} \dfrac{1}{N}\sum_{k=1}^{N} \phi_k \phi_k^{\mathrm{T}} \to R_u, \\ \left(\dfrac{1}{N}\sum_{k=1}^{N} \phi_k \phi_k^{\mathrm{T}}\right)^{-1} \to R_u^{-1}, \\ \dfrac{1}{N}\sum_{k=1}^{N} \phi_k d_k \to B, \end{cases} \quad (5)$$

where R_u and R_u^{-1} are positive definite, and

$$\hat{\theta}_N \to \hat{\theta} = \theta + R_u^{-1} B.$$

Proof Similar to the proof of Theorem 1, by ergodicity the sample means of the terms converge w.p.1 to their corresponding means

$$\begin{aligned} &\frac{1}{N}\sum_{k=1}^{N} \phi_k \phi_k^{\mathrm{T}} \to E\phi_k \phi_k^{\mathrm{T}} = R_u, \\ &\frac{1}{N}\sum_{k=1}^{N} \phi_k d_k \to E\phi_k d_k = B. \end{aligned} \quad (7)$$

The limiting equation $\hat{\theta} = \theta + R_u^{-1} B$ follows immediately. □

As a result of Theorem 2, accuracy of channel estimation depends critically on correlations between u_k and d_k. Fig. 5 shows deterioration of noise cancellation efficiency in lung sound analysis when correlations exist. The estimated sounds are obtained by ANC. A remedy for this problem is introduced in the next section.

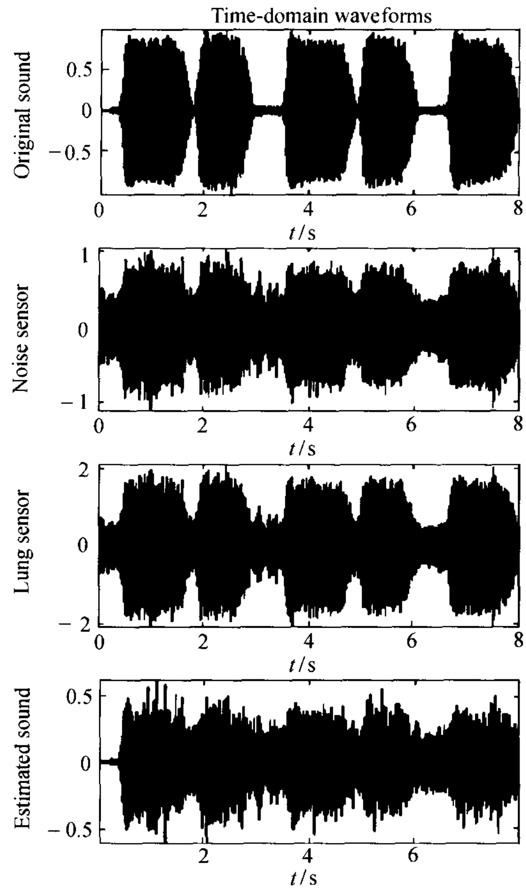


Fig. 5 Impact of correlation on noise cancellation.

4 Time-shared channel identification and modified adaptive noise cancellation

Return to the typical breathing pattern in Fig. 4. During the time from the end of exhale and the beginning of inhale, there is a pause interval in which lung sounds are very small. In other words, in that interval the lung sound y is nearly zero. While the overall breathing sounds are not stationary processes, signals that are confined in each stage are approximately stationary. Mathematically, if one extracts all inhale segments of a breathing sound and concatenate them into a single waveform, then this waveform is approximately stationary. We shall denote such signal segments as y^i for inhale sounds, y^e for exhale sounds, and y^p for pause sounds.

From Theorem 2, it is clear that to reduce estimation errors on channel dynamics, it is highly desirable to reduce B that consists of correlations c_m between u_k and d_k. It is observed that due to diminishing lung sounds during the pause interval, the vector B^p (corresponding to the correlation between y^p process and d) in the pause interval is much smaller than B^i and B^e for inhale and exhale processes, leading to our time-shared adaptive noise cancellation algorithm.

4.1 Time-shared identification and noise cancellation

The measured y_1 during the pause stage is essentially the output of the noise channel G in that interval. As a result, we can use input/output pair (y_2 and y_1) to identify G in this interval. This will not require any assumption on independence of y and y_2. This idea leads to the following lung sound/noise separation algorithms.

1) Initial channel identification:

During a pause stage, the measured y_2 (virtual input) and y_1 (output) are used to identify the noise channel $G(\theta)$, using a recursive algorithm. The estimated model will be denoted by $G(\hat{\theta}_0)$.

Step 1 Inhale and exhale stages.

At the k-th breathing cycle ($k = 0,1,2,\cdots$), during the T_i (inhale) and T_e (exhale) stages, the estimated noise channel model $G(\hat{\theta}_k)$ is used to extract the original lung sound via $y = y_1 - G(\hat{\theta}_k)y_2$.

Step 2 Transitional pause stage.

During the pause stage of the k-th breathing cycle, the estimated noise channel model is updated by using the new data from measured y_2 (virtual input) and y_1 (output). The channel model $G(\hat{\theta}_k)$ is used as the initial condition and the model is updated by a recursive algorithm (the RLS estimation in this paper), leading to an updated model $G(\hat{\theta}_{k+1})$.

2) Recursive steps:

In the $(k+1)$-th breathing cycle, go to Step1 with the newly updated channel model $G(\hat{\theta}_{k+1})$. These steps are then repeated from cycle to cycle.

This cycle-to-cycle recursion will be computationally very efficient since models are updated by using only new measurements and no past data need to be remembered. Also, by gradually discarding old data via, say, exponential discarding data windows, one can in fact track time-varying channel characteristics, that can be used in continuous monitoring and diagnosis of breath sounds.

4.2 Convergence analysis

In this subsection, we provide an analysis on convergence rates of the estimates. It will be shown that not only correlations result in estimation bias as evidenced by (6) they also reduce convergence rates significantly. Again in this aspect, it becomes favorable to choose an interval of smaller correlation for system identification since it entails a faster convergence rate.

To understand this, we start with the case of uncorrelated u_k and d_k. In this case, the large deviation theorems show that exponential convergence rates are guaranteed.

① Uncorrelated lung sound and noise.

Concentrating on a special case with the following assumptions: Suppose that u_k and d_k satisfy Assumption A1 and in addition u_k are i.i.d. Now, consider the error term $r_N = (\sum_{k=1}^{N}\phi_k d_k)/N$. A typical component of r_N is

$$z_N^e = \frac{1}{N}\sum_{k=1}^{N} u_{k+m}d_k.$$

Define, for an $\eta > 0$,

$$m(\eta) = \inf_{z\geqslant 0} \mathrm{e}^{-z\eta}E\{\mathrm{e}^{z(u_1 d_1)}\}.$$

The large deviations principles [19,20] ensure that: For any $\eta > 0$,

$$P\left\{\left|\frac{1}{N}\sum_{k=1}^{N} u_{k+m}d_k\right| \geqslant \eta\right\} \leqslant (m(\eta))^N. \tag{8}$$

For any $0 < \kappa < m(\eta)$ and for sufficiently large N

$$P\left\{\left|\frac{1}{N}\sum_{k=1}^{N} u_{k+m}d_k\right| \geqslant \eta\right\} \geqslant (m(\eta)-\kappa)^N. \tag{9}$$

Indeed, under the hypothesis, u_k and d_k are independent. As a result, $u_{k+m}d_k$ is zero mean and i.i.d. The inequalities (8) and (9) follow from the well-known large deviations theorems [20].

Remark 1 Inequality (8) shows that the estimation error due to noise converges to zero exponentially. Inequality (9) indicates how tight the exponential bounds can be. The moment generating function $E\{\mathrm{e}^{z(u_1 d_1)}\}$ depends on the actual distributions of u_1 and d_1. If $u_1 d_1$ is normally distributed, then $m(\eta) = \exp(-\eta^2/(2\sigma^2))$. It follows that in this case

$$(\mathrm{e}^{-\frac{\eta^2}{2\sigma^2}} - \kappa)^N \leqslant P\{|\frac{1}{N}\sum_{k=1}^{N} u_{k+m}d_k| \geqslant \eta\} \leqslant \mathrm{e}^{-\frac{\eta^2 N}{2\sigma^2}}. \tag{10}$$

Furthermore, by the central limit theorem, r_N is asymptotically normally distributed. As a result, for sufficiently large N, the convergence rates in (10) provide a good approximation even when the underlying distributions are not normal.

These results show that if signal and noise are independent, ANC is a very good identification scheme since the probability of large estimation errors is exponentially small.

② Correlated lung sounds and noises.

When u_k and d_k are correlated, a typical term

$$\frac{1}{N}\sum_{k=1}^{N} u_{k+m}d_k \to c_m \text{ w.p.1}.$$

Define $w_k = u_{k+m}d_k - c_m$. Then w_k satisfies $Ew_k = 0$. Now for $l \neq 0$,

$\gamma_l = Ew_k w_{k+l} = E(u_{k+m}d_k - c_m)(u_{k+m+l}d_{k+l} - c_m)$ may not be zero. Hence, in general w_k is not uncorrelated. However, if the correlation is of short memory, namely, γ_l is small in a certain sense, then convergence rates can be established.

Assumption A3 1) Assumption A2 is valid; 2) γ_l satisfies

$$b = \lim_{n\to\infty}\sum_{l=-n}^{n}\gamma_l(1 - |l|/n) < \infty.$$

Define $S_N = \sum_{k=1}^{N} w_k/N$. Assume the existence of the following moment generating functions and their limits

$$\Gamma_N(\lambda) =: \log E[e^{\lambda S_N}],\ \Gamma(\lambda) = \lim_{N\to\infty}\frac{1}{N}\Gamma_N(N\lambda). \tag{11}$$

Let $\Gamma^*(x)$ be the Fenchel-Legendre transform of $\Gamma(\lambda)$

$$\Gamma^*(x) = \sup_{\lambda\in\mathbb{R}}[\lambda x - \Gamma(\lambda)].$$

Theorem 3 Under Assumption A3 and existence of the function in (11),

$$\limsup_{N\to\infty}\frac{1}{N}\log P\{\|S_N\| \geq \eta\} \leq -\frac{\eta^2}{2b}.$$

Proof Under the hypothesis, by [19, Exercise 2.3.23, p.52] $\Gamma^*(x) = x^2/(2b)$ and it is a good rate function. Furthermore, by the Gartner-Ellis Theorem [19, Theorem 2.3.6, p.44]

$$\limsup_{N\to\infty}\frac{1}{N}\log P\{\|S_N\| \geq \eta\}$$

$$\leq -\inf_{|x|\geq\eta}\Gamma^*(x) = -\frac{\eta^2}{2b}.$$

□

From Theorem 3, it is clear that the probability of large estimation errors will be exponentially small with respect to N, namely

$$P\{\|S_N\| \geq \eta\} \leq \kappa e^{-\frac{\eta^2 N}{2b}}.$$

Obviously, the smaller the value b, the smaller the error probability since $\eta^2/2b$ defines the time constant of the exponential function. Now, from the expression $w_k = u_{k+m}d_k - Eu_{k+m}d_k$, the magnitude $|w_k|$ is proportional to the magnitude β of $|u_k| \leq \beta$. In turn b is proportional to β^2. As a result, selecting a time interval in which β is small will result in a faster convergence rate. This entails a motivation for our time-shared channel identification and modified adaptive noise cancellation.

4.3 Error bounds of the time-shared ANC

Theorems 2 and 3 provide a foundation for analyzing the benefits of the time-shared ANC. Consider the three signal processes y^i, y^e, y^p defined in the previous section, and the noise process d. Correspondingly, measured lung sounds are $x^i = y^i + Gu, x^e = y^e + Gu, x^p = y^p + Gu$. ANC relies on the same signal process for both identification and noise cancellation. For concreteness, assume the signal process is y^i. The time-shared ANC utilizes y^p for identification and y^i for noise cancellation. In both cases, the inputs are the measured virtual noise u.

Under Assumption A2, denote the correlation matrices in (4) by: B^i for correlation between u and y^i, and B^p for correlation between u and y^p. The auto-correlation matrix R_u varies slightly between the inhale phase and pause phase, and will be denoted by R_u^i and R_u^p, respectively. The channel estimate from ANC is

$$\hat{\theta}_N^i = \theta + (R_u^i)^{-1}B^i = \theta + r_N^i,$$

and the estimate from the time-shared ANC is

$$\hat{\theta}_N^p = \theta + (R_u^n)^{-1}B^p = \theta + r_N^p.$$

To be consistent with typical notation in identification, we will still use the symbol d (which is equal to the authentic lung sound y) in identification, but change it to y during noise cancellation to indicate signal extraction.

Applying these estimates to noise cancellation on the process y^i, we have

$$\begin{aligned}\hat{y}_k^{\text{anc}} &= x_k^i - \phi_k^{\mathrm{T}}\hat{\theta}_N^i\\ &= y_k^i + \phi_k^{\mathrm{T}}\theta - \phi_k^{\mathrm{T}}\hat{\theta}_N^i\\ &= y_k^i - \phi_k^{\mathrm{T}}r_N^i\end{aligned}$$

for ANC; and

$$\begin{aligned}\hat{y}_k^{ts\text{anc}} &= x_k^i - \phi_k^{\mathrm{T}}\hat{\theta}_N^p\\ &= y_k^i + \phi_k^{\mathrm{T}}\theta - \phi_k^{\mathrm{T}}\hat{\theta}_N^p\\ &= y_k^i - \phi_k^{\mathrm{T}}r_N^p\end{aligned}$$

for the time-shared ANC. Consequently, the errors in signal extractions are

$$e_k^{\rm anc} = y_k^i - \hat{y}_k^{\rm anc} = \phi_k^{\rm T} r_N^i, \text{ for ANC}$$

and

$$e_k^{ts\,\rm anc} = y_k^i - \hat{y}^{ts\,\rm anc} = \phi_k^{\rm T} r_N^p, \text{ for the time-shared ANC.}$$

Define $\| B^i \|_2 = \alpha^i$, $\| B^p \|_2 = \alpha^p$, $\bar{\sigma}(R_u^i)^{-1} = \beta^i$, $\bar{\sigma}(R_u^p)^{-1} = \beta^p$, where $\bar{\sigma}$ is the largest singular value of a matrix.

Theorem 4 1) The sample means of $(e_k^{\rm anc})^2$ and $(e_k^{ts\,\rm anc})^2$ converge, w.p.1, to $(B^i)^{\rm T}(R_u^i)^{-1}B^i$ and $(B^p)^{\rm T}(R_u^p)^{-1}B^p$, respectively.

2) The limits are bounded by

$$(B^i)^{\rm T}(R_u^i)^{-1}B^i \leqslant \beta^i(\alpha^i)^2,$$
$$(B^p)^{\rm T}(R_u^p)^{-1}B^p \leqslant \beta^p(\alpha^p)^2.$$

Proof 1) After N observations, the sample means of the errors are

$$\mu_N^{\rm anc} = \sum_{k=1}^{N} (e_k^{\rm anc})^2/N,$$
$$\mu_N^{ts\,\rm anc} = \sum_{k=1}^{N} (e_k^{ts\,\rm anc})^2/N.$$

These are exactly the sample mean square errors. By ergodicity and Theorem 2, they converge, w.p.1, to

$$\mu_N^{\rm anc} \to (B^i)^{\rm T}(R_u^i)^{-1}B^i,$$
$$\mu_N^{ts\,\rm anc} \to (B^p)^{\rm T}(R_u^p)^{-1}B^p.$$

2) Since $\sqrt{B^{\rm T}(R_u)^{-1}B}$ is the $(R_u)^{-1}$ weighted l^2 norm of B, we have

$$(B^i)^{\rm T}(R_u^i)^{-1}B^i \leqslant \beta^i(\alpha^i)^2.$$
$$(B^p)^{\rm T}(R_u^p)^{-1}B^p \leqslant \beta^p(\alpha^p)^2.$$

□

Theorem 4 states that the time-shared ANC can reduce signal reconstruction errors, in terms of mean square errors, by a factor of at least $\eta = \beta^i(\alpha^i)^2/\beta^p(\alpha^p)^2$. In the special case of $\beta^p = \beta^i$, the factor becomes $\eta = (\alpha^i/\alpha^p)^2$.

5 Applications to sound pattern analysis

This section presents some examples that demonstrate the utility of the method introduced in this paper. The data was collected through a sophisticated human patient simulator (HPS), manufactured by METI, Inc. The HPS allows us to create difficult medical scenarios to evaluate and improve our system. The HPS imitates breath sounds under different medical conditions, such as age, gender, lung functions, etc. Three electronic stethoscopes are used simultaneously to measure lung sounds (left and right lungs) and reference noise (on one shoulder). Noises are generated by conversations, music, and instrumentation. Noise levels are controlled by music volumes and conversation loudness. To further evaluate noise impact, a variety of noises with different noise characteristics (such as waveforms, frequency centers, and bandwidths) are added to measured signals before signal processing. These noises are either collected from operating rooms or generated by computer.

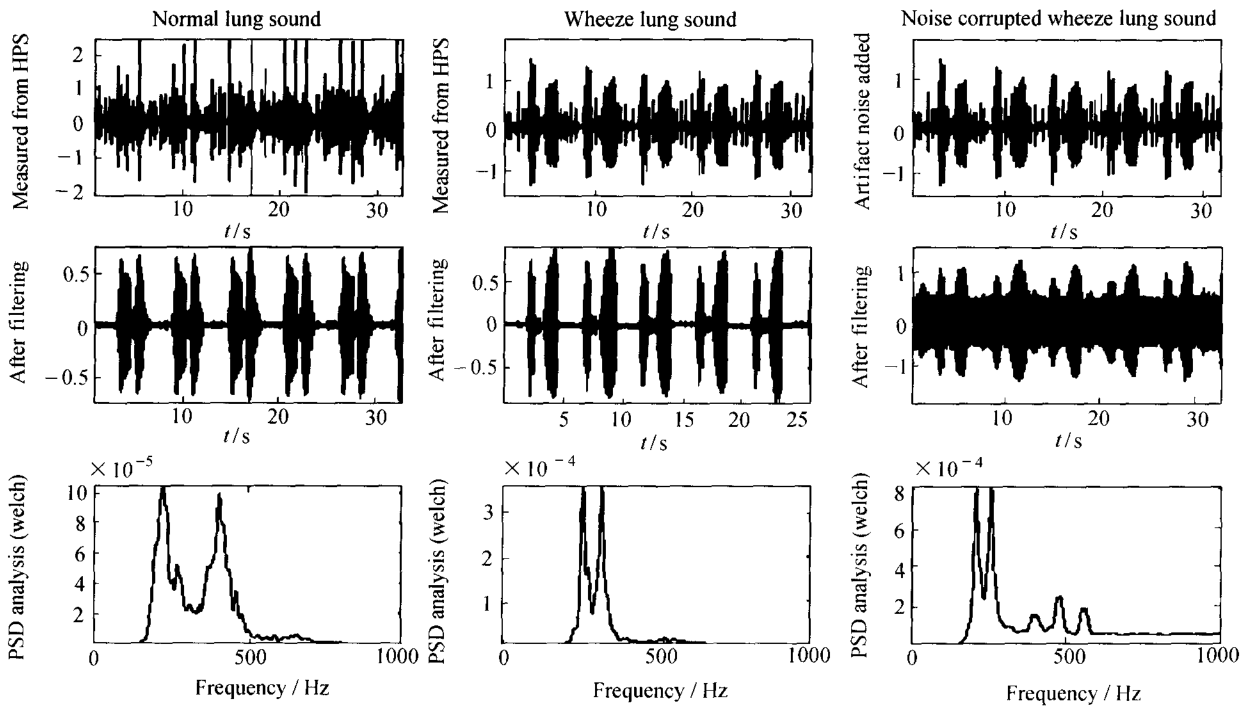
Noise sources pass through different transmission channels to influence both the lung-sound sensor and reference sensor. The structure and parameter values of these channels are not known to the identification algorithms. Since the noise reference sensor is placed in vicinity to the lung sensor, sound coupling may occur during data acquisition, leading to more severe signal/noise correlation. The system identification takes a black-box approach in which a discretized channel model with the regression representation (1) is used. These simulation studies include variations in noise types, frequency shifting, waveforms, and magnitudes.

5.1 Noise impact on sound characteristics

We shall start with an illustration of noise impact on lung sound patterns. Fig. 6(a) is a typical normal breathing sound and Fig. 6(b) an expirational wheeze. These are measured from the HPS, under the following scenarios: 1) The normal breathing sound is from a healthy 50-year old truck driver; 2) The wheeze is from a 50-year old smoker with lung disease. In both cases, patients are ventilated. To obtain typical sound patterns with minimum noise corruption, the environment noise was set as low as possible during data collection.

The top figures in Fig. 6 are the raw data measured directly from the HPS. Due to low-frequency noises from sensor contact surfaces, as pointed out in Section 2.1, the breathing patterns are not obvious. A high-pass filter is used to eliminate the noise under 200 Hz. After filtering, the difference between normal and wheeze lung sounds can be clearly seen from their time domain waveforms. In frequency domain analysis, the wheeze can be further characterized by a substantial narrowing of the spectrum, shifting of the center frequency (towards low pitch in this example), etc. For this example, sounds are obviously very clean with minimum noise corruption.

Sound patterns are significantly altered when noise artifacts are present. Fig. 6(c) shows the corrupted wheeze signal, both in its time-domain waveform and frequency-domain spectrum. It is apparent that in a noisy environment, the time-domain waveforms of a wheeze are distorted to the point that it is no longer possible to recognize sound patterns.



(a) Uncorrupted normal. (b) Uncorrupted wheeze. (c) Noise impact on wheeze.

Fig. 6 A normal sound and a wheeze, and noise impact on sound patterns.

5.2 Identification errors and convergence rates

It has been shown in Section 4 that not only estimation errors are highly dependent on the correlation between the input signal u_k and disturbance d_k, but also the convergence rates are effected significantly. In order to better understand this analysis, simulations were performed on identification errors of the recursive least-squares algorithm. Three cases were compared: 1) the input signal u_k is uncorrelated with the disturbance signal d_k; 2) u_k is correlated with k of a moderate level; 3) the correlation between u_k and d_k is more severe than the second case. Fig. 7 illustrates the trajectories of identification errors.

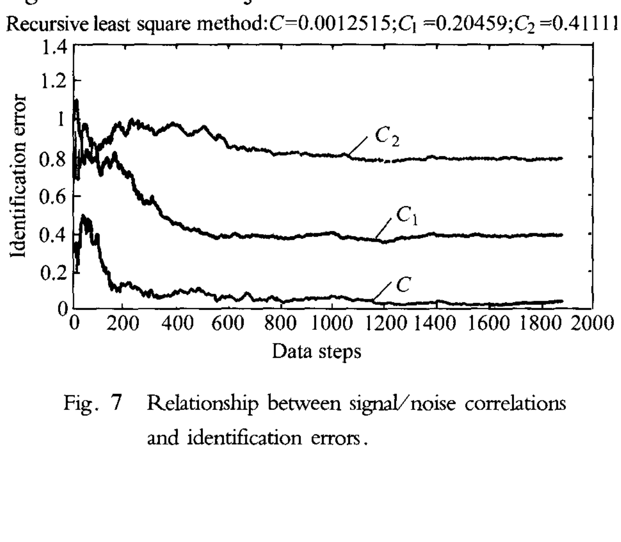


Fig. 7 Relationship between signal/noise correlations and identification errors.

The results clearly demonstrate that higher correlations between u_k and d_k lead to larger estimation errors and slower convergence rates. This simulation explains why our time-shared ANC method is more accurate and efficient.

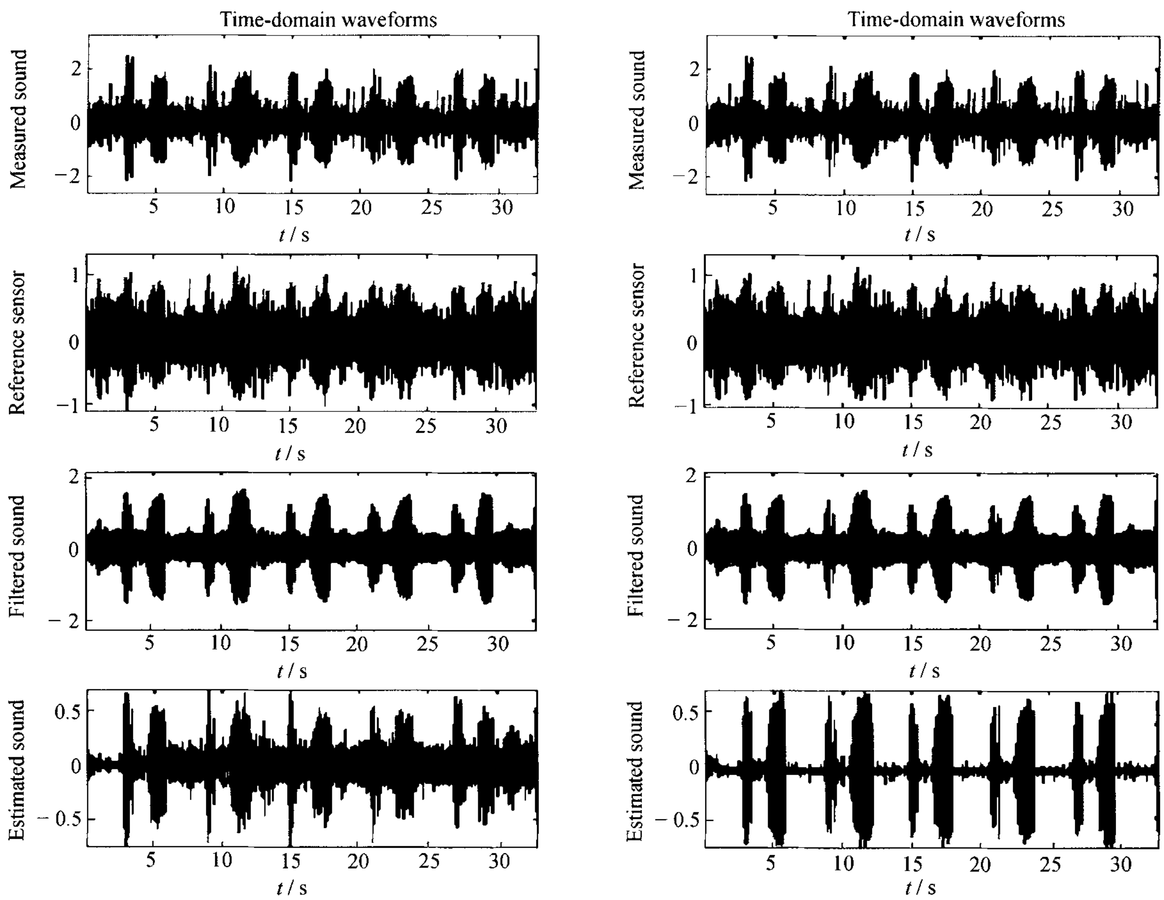
5.3 Channel identification

Here, we programmed a scenario on the HPS of a ventilated patient who is a 20-year old male soldier with wheezing breath sounds. Besides the background noise such as talking, alarming, and music, we also added some simulated noises to represent more severe frequency shifting and signal/noise correlation.

Noise transmission channels were identified by using both the traditional ANC and our time-shared identification methods. Their typical simulation results are presented in Fig. 8 (a) and (b), respectively. The lung sounds are measured directly from the HPS. These signals are corrupted by different noises with the resulting signals shown by the top plots in (a) and (b). The environment noises are, after passing through unknown transmission channels, measured by the reference sensor (the 2nd plots in (a) and (b)). In order to eliminate the off-band low frequency noises, both the measured lung signal and the reference signal pass through a designed high-pass filter. The after-filtering lung sound signals are shown by the 3rd plots in (a) and (b). The breathing sound stages of inhale, exhale, and pause can be distinguished by the averaged magnitude profiles from the 3rd plots in (a) and (b). Hence, switching between identification and noise cancellation will be derived from the filtered lung sound signals.

In application of ANC, a 30-th order moving average regression model is used in identification of the virtual channel. A recursive least-squares identification algorithm is used to update the parameters. The bottom plot in Fig. 8(a) is the estimated lung sound. Comparing with the typical wheeze plot in Fig. 6 (b), the estimated sound does not recover the original sound well.

In time-shared blind identification, we use the same regression model structure to identify the channel. While the lung sound is significantly corrupted by the noise, its envelope profile after filtering still retains an indication of its inhale, exhale, and pause stages. This profile information is used to divide each breathing cycle into the phases for identification or noise cancellation. During the identification phase (pause stage), a recursive least-squares identification algorithm is used to update the parameters in the regression model. During the noise-cancellation phase (inhale or exhale stages), the estimated regression model is used to derive noise estimates, which are then subtracted from the signal measured by the lung sensor. The process is then repeated in the next breathing cycle. The bottom plot in Fig. 8(b) is the estimated lung sound. The result is much better than the ANC method. We want to comment that there are some studies on time-domain lung sound patterns [21 ~ 23]. The noise corruption in lung sounds alters the sound waveforms significantly so that the time-domain wave patterns of the original lung sound are no longer apparent.

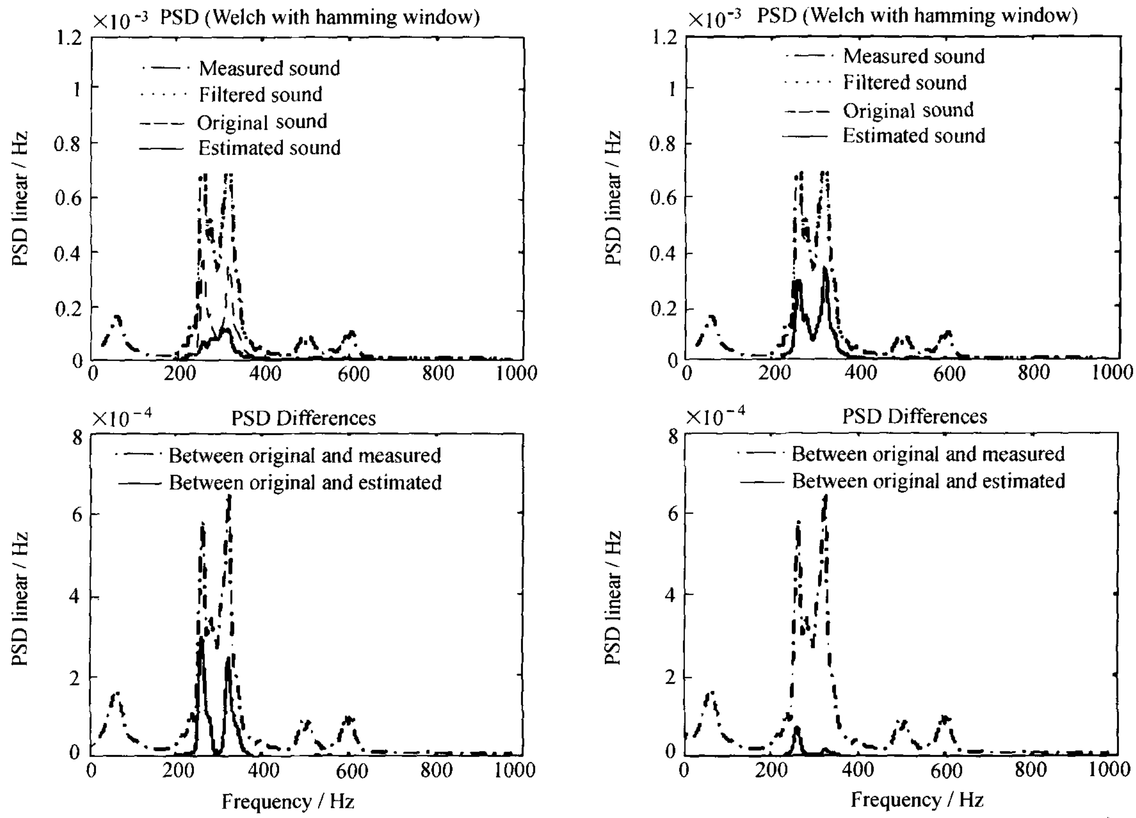


(a) Noise cancellation with ANC

(b) Noise cancellation with time-shared

Fig. 8 Time domain comparison of the ANC and time-shared ANC methods.

A better understanding of the effectiveness of our method is depicted in the frequency-domain comparison in Fig. 9. The noise spectrum overlaps with the lung sound spectrum. The estimated lung sound restores the power spectrum of the original lung sound. The bottom plots of (a) and (b) show effectiveness of noise reduction with the ANC and time-shared ANC methods. The results for ANC compare the spectra of the measured lung sound, estimated lung sound and original lung sound (the top plot of Fig. 9 (a)). ANC can only reduce noises that are not correlated with the lung sound in spectra, as shown in the bottom plot of Fig. 9 (a). Time-shared ANC provides a more effective noise reduction in spectra, as shown in Fig. 9 (b). It can cancel most noises no matter if they are correlated with lung sounds or not.



(a) Noise cancellation with ANC. (b) Noise cancellation with time-shared.

Fig. 9 Frequency domain comparison of ANC and time-shared ANC.

6 Concluding remarks

This paper introduces a new noise cancellation method for extracting authentic lung sounds from noisy auscultation environments. The method is unique in its utility of the breathing pause period for system identification and inhale/exhale phases for noise cancellation. As such it resolves a daunting challenge in this blind identification problem: noises may not be statistically independent of the lung sounds. This approach opens the opportunity of extending computer-aided lung sound analysis from acoustic lab settings to real clinical applications. This method complements the traditional filtering and ANC methods for noise reduction. As we have shown in this paper, combining this method with the traditional approach produces a more powerful tool than the individual utility of each method.

There are many open issues that can be studied in this direction. These include the effectiveness of the method in nonlinear noise transmission channels, sensor location selections, sensor configuration, impact of modeling distributed noises by lumped noises, etc. Also, the combination of this method with whitening (removing independent noises) can be further studied. However, the key foundation of this method seems to be sound in this application.

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