Lung Sound/Noise Separation for Anesthesia Respiratory Monitoring

Hong Wang[1], Le Yi Wang[2], Han Zheng[3], Razmig Haladjian[4], Meghan Wallo[5]
Department of Anesthesia[1,4,5], Department of Electrical and Computer Engineering[2,3],
Wayne State University
5050 Anthony Wayne Dr., MI 48202
United States of America

Abstract: - Noises are one of the key obstacles in applying continuous monitoring and computer-assisted analysis of respiratory sounds in operating rooms. This paper introduces a new methodology for extracting authentic lung sounds from a noisy environment. This methodology utilizes the unique feature of time-split stages in breathing sounds, rather than frequency separation or statistical independence. By employing a multi-sensor system, the method performs time-shared blind identification and noise cancellation with recursion from cycle to cycle. Since no frequency separation or signal/noise independence is required, this method can potentially provide a robust and reliable capability of noise reduction, and complement traditional filtering and whitening techniques. Its utility is evaluated by simulation and demonstrated by an application to monitoring of endotracheal tube positions using Human Patient Simulators.

Key-Words: -Blind identification, anesthesia monitoring, noise cancellation, respiratory sounds.

1 Introduction

This paper introduces a new method for blind identification of transmission channels in lung sound extraction problems. The method is derived on the basis of the unique nature of breathing sounds and can be used effectively in attenuating noise effects in lung sounds. When applied to anesthesia respiratory monitoring, the method can potentially enable computerized sound analysis in real clinical environment and enhance significantly accuracy and robustness in anesthesia diagnosis.

1.1 Motivation

Continuous monitoring of lung sounds is of essential importance in medical diagnosis for patients with lung diseases and detection of critical conditions in operating rooms. To obtain quantitative and reliable diagnosis and detection, it is critically important that respiratory auscultation retains sounds of high clarity. Clinical acoustic environment imposes 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 make operating rooms a very difficult acoustic environment. This paper introduces a new blind identification method that is unique to lung sound extraction from noisy environments. The system will consist of several lung sound sensors (special microphones, electronic stethoscopes, etc.) and a noise reference sensor. Our method conducts blind channel identification during the pausing intervals in breathing cycles and performs noise cancellation during inhale and exhale. Its application in anesthesiology is studied by some cases involving detection of endotracheal tube misplacements. Importance of noise attenuation in diagnosis accuracy in these cases will be illustrated.

1.2 Background

Noises are well known to be a fundamental challenge in developing automated lung sound analysis Traditionally, studies of heart and lung sounds have concentrated on filtering techniques. To further enhance the performance of the filtering process, FFT, power spectrum density, bi-spectrum analysis, wavelet analysis, high-order statistics, and stochastic averaging have been investigated extensively for their effectiveness in noise filtering and sound separation [1,2,3,4,10]. Frequency-domain filtering is applicable for reducing off-band noise (those with frequencies outside the signal frequency band). Another class of noise cancellation methodologies relies on stochastic independence [5,6,7,16]. Consider a respiratory sound measurement system in Figure 1. The main ideas of stochastic whitening are: (1) First generate from *y1* and *y2* the signals *w1* and *w2* that are statistically as independent as possible. (2) Then, *w1* is viewed as an estimate of the sound *y*. This method is effective only for independence noises and cannot capture any gains or nonlinear static mapping in the transmission media.

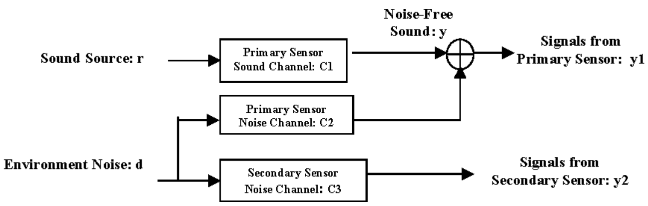


Fig.1: Sound Channels

We will develop an innovative noise reduction methodology that is uniquely designed to overcome the above key difficulties. Since our method does not rely on frequency band separation or statistical independence between lung sounds and noises, it can provide a more robust noise cancellation in this application. We should emphasize that application of our method does not exclude filtering or whitening methods. In other words, one may elect to apply target filtering by using both frequency filters and white noise separation after employing our method.

2 Method

For lung sound extraction problems, the noise transmission channels must be identified. Since noises cannot be measured at source, it is a blind identification problem.

2.1 Time-Split Blind Channel Identification

Our idea is to introduce a virtual noise framework and to use a time-split method to identify the system and to achieve noise cancellation. The noise reference sensor, which is placed in vicinity to the lung sensors, receives noises from all sources just like the lung sensors, but does not receive lung sounds. If we view *y2* as a virtual noise source, we may replace distributed noise sources in a lumped noise source *y2*, as shown in Fig. 2. Noise cancellation is now reduced to identification of the virtual noise channel *G* (in Fig. 1, *G* is the inverse of *C3* followed by *C2*). Indeed, given estimated *G*, the noise-free lung sound *y* can be approximately extracted as $y = y1 - G\, y2$.

Identification of *G* remains a difficult problem since *y* and *y2* may be correlated. Without a direct output measurement of the channel *G*, all existing identification methods fail to apply. Our approach in resolving this central issue is based on a simple observation: Ventilation or breathing cycles undergo the stages of inhale, exhale, and transitional pause. In between exhale and inhale, there is a pausing interval in which lung sounds are very small. Consequently, the measured *y1* is actually the output of the noise channel *G* in that interval. As a result, we can use input/output pair (*y2* and *y1*) to identify *G* in the interval. This will not require any assumption on independence or frequency separation. This idea leads to the following lung sound/noise separation algorithms.

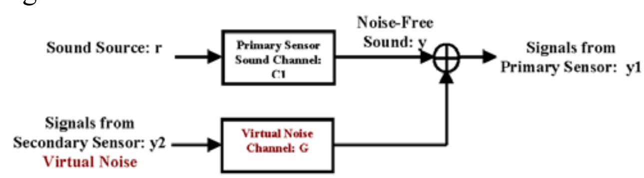


Fig.2: Virtual Noise Formulation

2.2 Lung Sound/Noise Separation

For signal processing, a ventilation or breathing cycle is divided into three stages: Inhale (Ti), exhale (Te), and transitional pause (T-Ti-Te). 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. For the virtual noise configuration shown in Fig. 2, let *G* be parametrized by a parameter vector θ, denoted by $G(\theta)$. Most commonly used parametrization is the ARMAX model (auto-regression, moving average, external input). The parameter vector θ is to be identified. The algorithm can be described as follows.

Initial Channel Identification:

During a pause stage, the measured *y2* (virtual input) and *y1* (output) are used to identify the noise channel $G(\theta)$, using a recursive algorithm, that will be detailed later. The estimated model will be denoted by $G(\theta_0)$.

Step 1: Inhale and Exhale Stages

At the *k*-th breathing cycle ($k=0,1,2, \ldots$), during the Ti (inhale) and Te (exhale) stages, the estimated noise channel model $G(\theta_k)$ is used to extract the original lung sound via $y = y1 - G(\theta_k)\, y2$.

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 *y2* (virtual input) and *y1* (output). The channel model $G(\theta_k)$ is used as the initial condition and the model is updated by a recursive algorithm, leading to an updated model $G(\theta_{k+1})$.

Recursive Steps

In the *(k+1)*-th breathing cycle, go to Step 1 with the newly updated channel model $G(\theta_{k+1})$. 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.

2.3 Recursive Identification Algorithms

We now provide some details on recursive algorithms. There are many possible choices. The following four are most commonly used in applications and have been tested by the authors in anesthesia applications. Consider an ARMAX model for G

y_t = the value of $y1$ at time index t

u_t = the value of $y2$ at time index t

$$\phi_t = [u_t, u_{t-1}, \cdots, u_{t-n+1}]^T \qquad (1)$$

θ = the n-dimentional parameter vector

Regression model of $G(\theta)$:

$$y_t = \phi_t^T \theta + w_t$$

The following recursive algorithms can be used to update the parameter vector θ.

Adaptive Filtering:

$$\theta_{t+1} = \theta_t + \frac{c}{t^r}\phi_t (y_t - \phi_t^T \theta_t), \qquad 0 < r \le 1$$

Adaptive Filtering with Averaging:

$$\hat{\theta}_{t+1} = \theta_t + \frac{c}{t^r}\phi_t (y_t - \phi_t^T \hat{\theta}_t), \qquad 0 < r \le 1$$

$$\theta_{t+1} = \theta_t - \frac{1}{t+1}\theta_t + \frac{1}{t+1}\hat{\theta}_{t+1}$$

One-Step Optimal Projection:

$$\theta_{t+1} = \theta_t + r\frac{\phi_t}{a + \phi_t^T \phi_t}(y_t - \phi_t^T \theta_t)$$

Recursive Least-Squares:

$$K_t = \frac{P_t \phi_t}{1 + \phi_t^T P_t \phi_t}; \;\; P_{t+1} = (I - K_t \phi_t^T) P_t$$

$$\theta_{t+1} = \theta_t + K_t (y_t - \phi_t^T \theta_t)$$

Theoretical properties of these algorithms have been extensively studied, especially their convergence and convergence rates. We refer the reader to [9] for further theoretical details.

3 Illustrative Examples

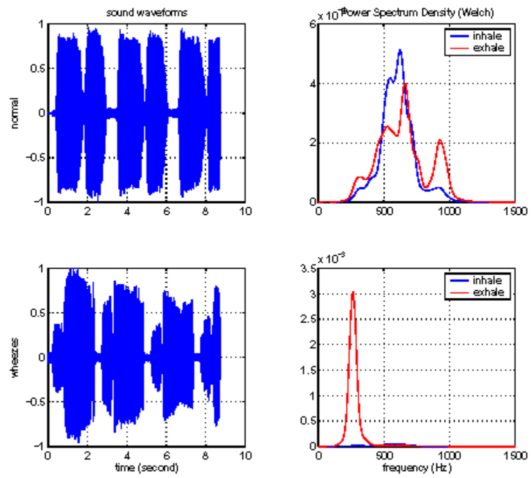
This section presents some illustrated examples that demonstrate the utility of the method introduced in this paper. To provide flexibility in evaluating our method, extensive simulation has been performed. The system includes several noise sources with different characterizations (such as waveforms, frequency centers, and bandwidth), waveforms collected from real environment, as well as computer generated random noises. Noise sources pass through several different transmission channels to influence the lung-sound sensor and reference sensor. The structure and parameter values of these channels are not known to the identification algorithms.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.

3.1 Noise Impact on Sound Characteristics

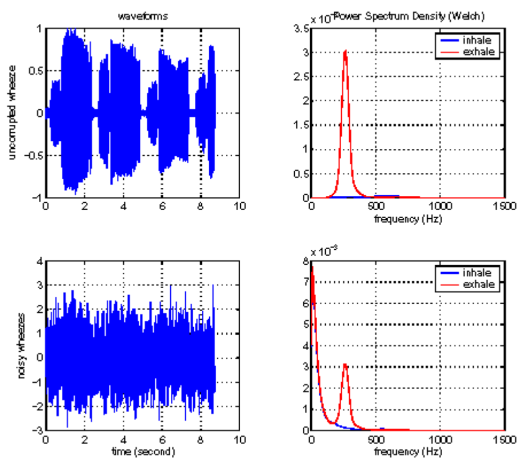
We shall start with an illustration of noise impact on lung sound patterns. Fig. 3(a) illustrates a typical normal breathing sound and an expirational wheeze (these are from the public respiratory sound database of Music Department of McGill University). For this example, the wheeze can be clearly characterized by a substantial narrowing of spectrum, shifting of center frequency (towards low pitch in this example), and power imbalance of inspiration and expiration. For this example, sounds are obviously very clean with minimum noise corruption. Sound patterns are significantly altered when noise artifacts are considered. Fig. 3(b) shows the corrupted wheeze, both in its time-domain waveforms and frequency-domain spectrum. It is clear 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.

3.2 Channel Identification

Here, we consider "natural breathing" patients in which the phases of "inhale," "exhale," and "pause" are mainly reflected in the sound power or averaged magnitude profiles. Hence, switching between "identification" and "noise cancellation" will be derived from lung sound signals.



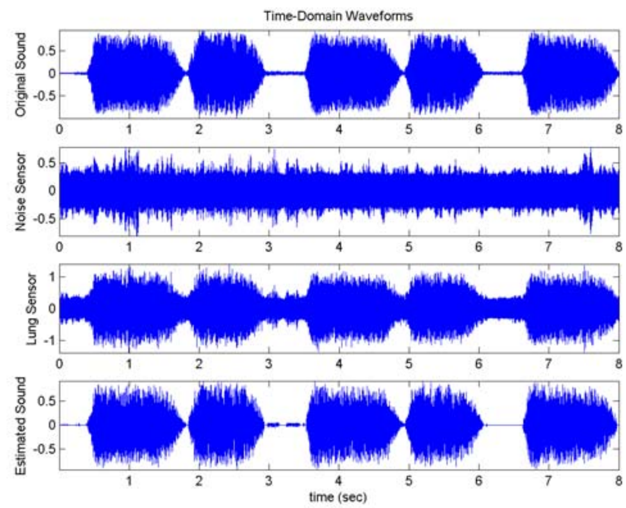
(a) Uncorrupted Lung Sounds



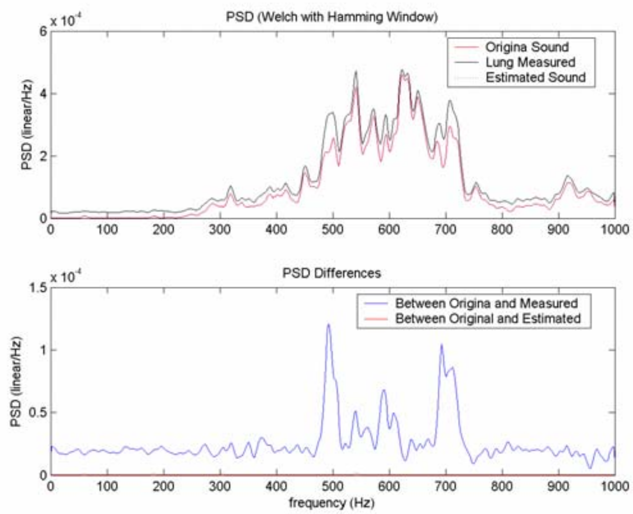
(b) Noise Impact on the Wheeze

Figure 3 A Normal Sound and a Wheeze, and Noise Impact on Sound Patterns

Figure 4 presents a typical simulation result. The original lung sound is a typical normal breathing waveform (the top plot in (a)). The environment noise is, after passing through an unknown transmission channel, measured by the reference sensor (the 2nd plot in (a)). The lung sound sensor is corrupted by environment noises with its signal denoted by the 3rd plot in (a). While the lung sound is significantly corrupted by the noise, its envelope profile 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. In this simulation, a 30-th order moving average regression model is used in identification. During the identification phase, a recursive least-squares identification algorithm is used to update the parameters in the regression model. During the noise-cancellation phase, the estimated regression model is used to derive the noise estimate which is then subtracted from the signal measured by the lung sensor. The process is then repeated in the next breathing cycle. The bottom plot is the estimated lung sound. We just want to comment that there are some studies on time-domain sound patterns [8,11,12]. The noise corruption in this simulation alters the sound waveforms significantly so that the time-domain wave patterns of the original lung sound are no longer apparent.



(a) Time-Domain Features



(b) Frequency-Domain Features

Figure 4 Channel Identification and Noise Cancellation

A better understanding of the effectiveness of our method is depicted in the frequency-domain comparison in Fig. 4(b). The noise spectrum overlaps with the lung sound spectrum. The estimated lung sound restores the power spectrum of the lung sound The bottom plot of (b) shows effectiveness of noise reduction. In terms of power levels, the lung sound measurements contain 15-25% noises, which are largely removed via this method.

4 Monitoring of Endotracheal Tube Positions

Unlike the class of “natural breathing” cases, if a patient is ventilated in anesthesia the breath pattern switching from “inhale” to “exhale” and then to “pause” is controlled by a ventilator. Consequently, switching between “identification” and “noise cancellation” can be directly derived from ventilation variables, such as airflow pressure changes. Lung sounds can be used to monitor endotracheal tube positions. A proper intubation will have the tube positioned in tracheal. As a result, oxygen will be ventilated into both lungs. This implies that breathing sounds from both lungs should be present. When the tube is either misplaced or drifted into one side of the lungs, bronchial intubation occurs. In bronchial intubation, only one side of the lungs is properly ventilated, while the other receives no oxygen supply. Bronchial intubation has dire clinical consequences and must be promptly detected.

Bronchial intubation is reflected by imbalanced sound intensities between the left and right lungs. Fig. 5 shows a case study involving noise-corrupted lung sounds in a patient (20-year-old healthy soldier simulated on the Human Patient Simulator from METI, Inc.).

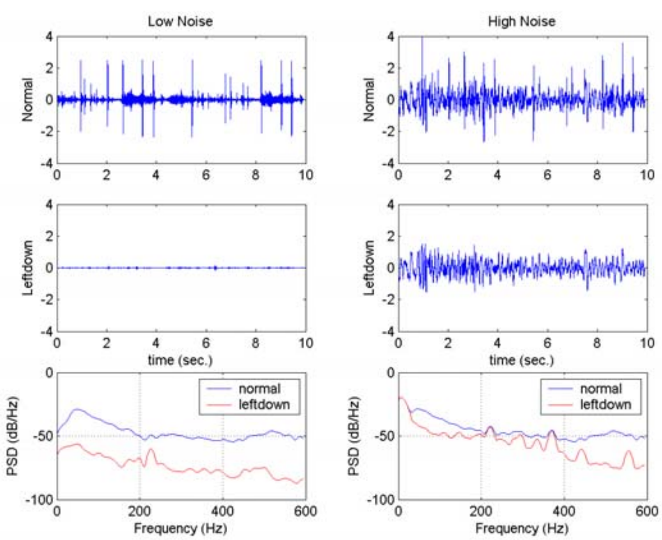


Figure 5: Monitoring of Bronchial Intubation

In this study, artificially-created right bronchial intubation with different degrees of reduced lung sounds is used. The simulation setting contains two lung sensors, one for the left lung and one for the right lung, as well as a noise reference sensor. All sensors are electronic stethoscopes in this study.

Without noise corruption, one may simply observe the sound powers from both lung sounds and compare their relative intensities, as shown in the bottom-left plot of Fig. 5. When power or intensity imbalance reaches a pre-designed threshold, a diagnosis of bronchial intubation may be prescribed. However, noises will have a detrimental impact on this approach. When high noise levels are experienced, the difference in power spectrum densities diminish, as shown in the right-bottom plot of Fig. 5.

Table 1 summarizes some typical power levels of lung sounds for bronchial intubation monitoring in a patient simulation, in which left bronchial intubation was introduced. The power of the left lung sound, that always receives oxygen and is not affected by the tube migration, is normalized at 100%. Then the relative power level of the right lung sound reflects the severity of tube migration. The lower the percentage shift, the lower the oxygen ventilation level to the right lung. If the lung sounds are not corrupted by noise, one can select a detection threshold, say, 65% for detecting bronchial intubation. The following table is one result from the simulations. The 2nd and 3rd columns indicate the power levels of left and right lung sounds under noise-free environment.

	No Noise	No Noise	Noisy	Noisy
Relative Sound Reduction	Left Lung	Right Lung	Left Lung	Right Lung
90%	100	90	100	95
50%	100	50	100	87
20%	100	20	100	78

Table 1. Power Levels of Lung Sounds

The last two columns of the table show changes in power levels when noises are added. Due to severe noise corruption, this detection problem becomes much more difficult. For example, if the detection threshold is set at, say, 65%, then noise artifacts will make the detection algorithm miss even the complete right-lung bronchial intubation. It should be emphasized that since this is a stochastic detection problem, reliability and accuracy of bronchial intubation detection can be assessed by the probabilities of "false alarm" and "missed detection," both must be small. Consequently, shifting threshold for alarm will simply increase one probability and reduce the other. Hence, it will not enhance overall detection accuracy. Also, unlike standard statistics in which the sample size can be used in reducing impact from randomness, detection accuracy in this application cannot be improved by using more breathing cycles. This is due to the persistent nature of noises. It seems that the only remedy for detection accuracy is to reduce noise effects by signal processing methods.

5 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 have similar frequency bands as the lung sounds and may not be statistically independent to the lung sounds. This approach opens the opportunity of extending computer-aided lung sound analysis from acoustic lab settings to real clinical applications.

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

References:

[1] Charleston, S.; Azimi-Sadjadi, M.R.; Gonzalez-Camarena, R., Interference cancellation in respiratory sounds via a multiresolution joint time-delay and signal-estimation scheme, *Biomedical Engineering, IEEE Transactions*, Oct. 1997, pp.1006 – 1019.

[2] Gavriely N. Nissan M. Rubin AH. Cugell DW. Spectral characteristics of chest wall breath sounds in normal subjects. *Thorax*. 50(12), 1995 Dec, pp.1292-1300.

[3] Hadjileontiadis, L.J.; Panas, S.M. Adaptive reduction of heart sounds from lung sounds using fourth-order statistics. *IEEE Transactions on Biomedical Engineering*, 44 (7), 1997, pp.642-648.

[4] Hadjileontiadis, L.J.; Panas, S.M. Adaptive reduction of heart sounds from lung sounds using wavelet-based filter. *Stud. Health Technol. Inform*. 43 (Part B), 1997, pp.536-540.

[5] S. Haykin, *Adaptive Filter Theory*, Prentice-Hall, Englewood Cliffs, NJ, 1990.

[6] S. Haykin, ed. *Unsupervised Adaptive Filtering*, Vol. I and II, John Wiley & Sons, Inc., 2000.

[7] Kompis M. Russi E. Adaptive heart-noise reduction of lung sounds recorded by a single microphone. *Proc. Annual International Conference of the IEEE*, Vol. 2, 1992, pp. 691-692.

[8] Lehrer S. *Understanding Lung Sounds*, 3rd ed., W.B. Sounders, 2002.

[9] L. Ljung, *System Identification: Theory for the User*, Prentice-Hall, Englewood Cliffs, NJ, 1987.

[10] Lu YS. Liu WH. Qin GX. Removal of the heart sound noise from the breath sound. *Engineering in Medicine and Biology Society*, Proceedings of the Annual International Conference of the IEEE, vol.1, Nov. 1988, pp. 175 - 176.

[11] Pasterkamp H. Kraman S. Wodicka G. Respiratory sounds. Am. J. *Respir Crit Care Med*. Vol. 156, 1997, pp.974-987.

[12] Sovijarvi AR. Helisto P. et al A new versatile PC-based lung sound analyzer with automatic crackle analysis (HeLSA); repeatability of spectral parameters and sound amplitude in healthy subjects. *Technology & Health Care*. 6(1), 1998 Jun, pp. 11-22.

[13] Wang H. and Wang LY., Continuous Intro-Operative Respiratory Auscultation in Anesthesia, *IEEE Sensors 2003*, Toronto, Oct., 2003.

[14] Wang H. and Wang LY., Multi-Sensor Adaptive Heart and Lung Sound Extraction, *IEEE Sensors 2003*, Toronto, Oct., 2003.

[15] Wang LY., Yin G., and Wang H., Nonlinear system identification in medical applications, *SYSID 2003*, Rotterdam, The Netherlands, August 27-29, 2003.

[16] B.Widrow and S.D. Stearns, *Adaptive Signal Processing*. Prentice-Hall, Englewood Cliffs, NJ, 1985.