WHEEZE RECOGNITION BASED ON 2D BILATERAL FILTERING OF SPECTROGRAM

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ABSTRACT

This paper describes the design of a low-cost and high performance wheeze recognition system. First, respiratory sounds are captured, amplified and filtered by an analog circuit; then digitized through a PC soundcard, and recorded in accordance with the Computerized Respiratory Sound Analysis (CORSAs) standards. Since the proposed wheeze detection algorithm is based on the spectrogram processing of respiratory sounds, spectrograms generated from recorded sounds have to pass through a 2D bilateral filter for edge-preserving smoothing. Finally, the processed spectra go through an edge detection procedure to recognize wheeze sounds.

Experiment results show a high sensitivity of 0.967 and a specificity of 0.909 in qualitative analysis of wheeze recognition. Due to its high efficiency, great performance and easy-to-implement features, this wheeze recognition system could be of interest in the clinical monitoring of asthma patients and the study of physiological mechanisms in the respiratory airways.

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Keywords: respiratory sound; CORSAs; wheeze; spectrogram; bilateral filter

1. INTRODUCTION

Pulmonary disease is a major cause of ill-health throughout the world. In Europe, chronic obstructive pulmonary disease (COPD) and asthma have been estimated to affect between 10 and 25% of adult population. In many countries roughly 5% of the populations suffer from asthma and other related chest disorders [1]. Wheezes have been reported as adventitious respiratory sounds in asthmatic or obstructive patients, during forced exhalation maneuvers. Wheezes are musical adventitious lung

sounds, also called “continuous” since their duration is much longer than that of “discontinuous” crackles. The waveform of a wheezing sound contains one or several sinusoidal components. This justifies the musicality of wheezes; hence, distinct peaks can be observed in the frequency domain [2]. According to the new definitions of the present CORSAs standards, the dominant frequency of a wheeze is usually greater than 100Hz and the duration is greater than 100ms [3]. Wheezes can be monophonic, when only one pitch is heard, or polyphonic when multiple frequencies are simultaneously perceived. The transmission of wheezing sound through the airways is better than transmission through the lung to the surface of the chest wall. The higher frequency sounds are more clearly detected over the trachea than at the chest [4]. The high frequency components of breath sounds are absorbed mainly by the lung tissue [5]. The frequency

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content of wheezes lies within the frequency range of 100-2500Hz.

Wheezes, which are louder than the underlying breath sounds, are often audible at the patient's open mouth or by larynx auscultation. However, in clinical practice, some difficulties are verified during diagnosing elaboration, such as sensitivity difference between the ears; young or aged physician's experience and skill. Furthermore, some sounds which may be diagnostically important may be overshadowed and lost due to more intense background sounds produced by other chest functions. The computerized analysis of lung sounds allows a reproducible quantification of wheezing, in contrast to subjective auscultation [6].

Among techniques to study respiratory sounds, different algorithms have been developed to detect and analyze wheezes. The most straightforward methods for automatic detection are based on searching for peaks in frequency domain [7-11]. When studied with spectral analysis, wheezes are seen as narrow peaks in the power spectrum, generally below 2000Hz. The diagnostic failures occur frequently because of dominant frequency of a wheeze may shift or when noise power is greater than wheezes. The algorithms used in these studies are quite simple and fast, however, they are not very reliable and sensitive. In order to increase sensitivity of detecting wheezes based on successive spectra, some algorithms combined with classification models are proposed [12-14]. These approaches can improve wheezing recognition by using feature extraction and comparison. The coefficients of classification models have to be adjusted empirically, thus increasing the complexity of algorithms and causes inconvenience. The algorithms combined with classification models provide more precise but slower wheezing detection. Recent attempts for achieving higher sensitivity and efficient detection performance include a set of criteria in the time-frequency domain [15-17]. These criteria refer to time duration, pitch range and magnitude of wheezes in their time-frequency representation by means of spectrogram analysis. The aim of these studies was to automatically locate and identify wheezing episodes during sound recordings according to some well-defined criteria. These thresholds criteria are used several times to empirically generate a normalized spectrum for the detection of a maximum number of spectrum peaks not related to the background noise. Thus, it is difficult to accomplish reproduction of a wheezing detection system in different measuring environments. Spectrogram, also called respirosogram, was largely used for auscultation teaching and lung sounds researches, it was also proposed to detect wheezes [18]. The aim of this study is to investigate a method for recognizing lung sounds applying techniques of image processing based on the

normalized spectrogram recorded from lung sound. The method proposed increases the visualization of the wheezing picture characteristics and uses them to search for horizontal or nearly horizontal edges of the spectrogram. In this way, the wheezing recognition severely depends on image processing skills and spectrogram resolution. Very short wheezes were not detected.

In this study, we have constructed a low-cost hardware system to record respiratory sounds and store them as a wave file. The high-amplitude components of the spectrogram of the sounds are selected and then passed through a 2D bilateral filter to reduce noise and preserve the spectrogram edges. The filtered spectrogram is sent to two parallel processing paths. The first path extracts significant wheeze episodes from background noise. The second path performs the edge detection and restructures the rough wheeze episodes that can be used as a mask. The processed image from the first path passes through a mask generated from the second path finally to form a wheeze episode. The study proposed uses simple approaches to enhance the features of wheeze even at low intensities and classifies wheeze-with and wheeze-without that not requiring air flow data.

2. HARDWARE ARCHITECTURE

2.1. Respiratory Sound Capturing System

Many different types of equipment and techniques exist for acquisition of respiratory sounds [19]. Our proposed system was developed in accordance with CORSA standards and previous studies [20-28]. Fig. 1 shows a diagram of the respiratory sound capturing system. The analog processing system consists of a sensor, a pre-amplifier, a band-pass filter (BPF) and a final amplifier prior to analog-to-digital conversion (ADC). The purpose of using a BPF is to reduce the heart, muscle and contact noises. The amplifiers are

Fig. 1. Block diagram of the respiratory sound capturing system.

used to increase the amplitude of the captured signal such that the full ADC range can be optimally used, and sometimes to adjust the impedance of the sensor.

2.2. Sensors

A microphone detects air pressure variations, which are converted into electrical signals by movements of the microphone diaphragm. The sound sensor was realized using an electret condenser microphone (ECM, KEC-2738, Kingstate Electronics Corp., Taipei, Taiwan) with a bell of stethoscope (3M Littmann Classic S. E.) fixed by hand between the skin surface and the microphone. This omni-directional ECM sensor provides a fairly high signal-to-noise ratio (SNR), high sensitivity, and frequency response that is flat in the band of interest.

2.3. Pre-amplifier and Final Amplifier

Pre-amplifier is used to amplify the sensor signal to an appropriate range for the following filter stage, and also to adjust the impedance of the sensor. An INA128P (Texas Instruments, USA) was used in our application and conformed with the CORSA recommendation. This pre-amplifier, used in a differential mode with unity gain and a supply voltage of $\pm 5V$, can serve as an amplifier stage for the ECM sensor. Regarding the final amplifier, its purpose is to amplify the filtered signal such that the full ADC range can be optimally used. We cascaded two inverting amplifiers as a final amplifier.

2.4. Filters

Some distortions are typically produced by changes in the contact pressure of the sensor cup due to patient or sensor motion, by heart sounds, muscle noise, and external low frequency noise. In order to reduce the heart, muscle and contact noises, and to prevent ADC from saturation while preserving the useful respiratory sound components, our designed bandwidth is from 60Hz to 4 kHz for both lung and trachea sound analysis. A Butterworth low-pass filter (LPF) of fourth-order with 4kHz cut-off and a fourth-order Bessel high-pass filter (HPF) were used to form the band-pass filter (BPF). One single Quad Op-amp (MC34074, Motorola, Inc., USA) is used in both the HPF and LPF implementations, to be connected as 4 active filter stages (each of order 2) in cascade.

2.5. Digitization of Sound

The digitization of sound was performed by a soundcard (CS4297A) bounded in an IBM laptop (A22M, P-III 1GHz). A 2kHz bandwidth appears to be sufficient for studies of wheeze, extending the bandwidth up to 4kHz is a perfect choice for both the

analysis of most adventitious sounds and upper-airway sounds. When it comes to wheezing sound analysis, a simply standardized decimation strategy for reducing the sampling, digitally, to say 5.125kHz could be used [7]. A standardized sampling rate applied in many industry standard sound facilities is 44.1kHz, which is rather high for respiratory sound studies. Therefore, many researchers have been using sub-multiples of 44.1kHz, i.e. 22.05, 11.025 or 5.5125kHz as standards. In our proposed system, we set the sampling rate at 22.05kHz.

3. ALGORITHM FOR WHEEZE EPISODE DETECTION

3.1. Overview of Wheeze Episode Detection

The musical wheezing characteristics are determined by a fundamental frequency and its harmonics. As these characteristics are continuous, the resulting spectrogram presents quasi-horizontal lines that define a strong presence of a determined frequency during a period of time. We can easily distinguish wheeze episodes as distinct edges from background sound components in Fig. 2 which shows a segment of typical tracheal wheezing sound in the spectrogram. However, the edges that represent wheeze episodes are difficult to recognize by computer due to blurred edges or spots formed with noise. In order to solve these problems, we developed a wheeze detecting algorithm based on 2D bilateral filtering of a spectrogram to reserve the edges that define wheeze episodes and to eliminate other unwanted noises. Fig. 3 outlines an overview of the wheeze episode detecting process. The system first needs to generate a spectrogram from a wave file that records several respiratory cycles. The spectrogram passes through a limiter to preserve the highest power spectra, then through a 2D bilateral filter in two iterations to enhance the quasi-horizontal lines and blur the small objects. The image filtered by the 2D bilateral filter is sent to two individual paths: the right side path in Fig. 3 processes edge detection and quasi-horizontal lines reconstruction to form a mask, the left side path combines several power level spectrograms into a binary image that only preserves high and isolated amplitudes. The image combined from the left path and passing through the mask will remove unacceptable objects that do not have shapes of quasi-horizontal lines. Eventually, the quasi-horizontal lines separated from the spectrogram can easily be recognized as wheeze-with or wheeze-without sound.

Fig. 2. A segment of typical tracheal wheezing sound in time-frequency domain representation of spectrogram.

Fig. 3. Overview of wheeze episode detecting process.

3.2. Edge Reserving Filter

The most important procedure of wheeze episode detection is the 2D bilateral filtering [29-32]. The bilateral filter was first intuitively proposed by Tomasi and Manduchi in 1998 as an alternative non-iterative tool for noise removal. This filter is simply a weighted average of the local neighborhood samples, where the weights are computed based on spatial and radiometric distances between the center sample and the neighboring samples. This filter is also locally adaptive, and it was shown to give better results than those obtained by the iterative approaches such as anisotropic diffusion (AD), weighted least squares (WLS), and robust estimation (RE). Their comparison is summarized in Table I.

Table I. Comparison of bilateral filter, WLS, RE, AND AD

Feature	Bilateral filter	WLS/RE/AD
Behavior	Edge preserving	Edge preserving
Support Size	May be large	Very small
Iteration	Possible	Must
Origin	Heuristic	MAP-based
Efficiency	High	Low

In order to simplify the notations we stick to the 1D case throughout this paper, though all derivations apply to the 2D case as well. An unknown signal $\underline{X}$ represented as a vector goes through a degradation stage in which a zero-mean white Gaussian noise $\underline{V}$ is added to it. The result is the corrupted signal $\underline{Y}$ given by

$$\underline{Y} = \underline{X} + \underline{V} \quad (1)$$

Our task is to remove this noise and restore $\underline{X}$, given the degraded signal $\underline{Y}$. The bilateral filter suggests a weighted average of pixels in the given image $\underline{Y}$ in order to recover the image $\underline{X}$.

$$\hat{X}[k] = \frac{\sum_{n=-N}^N W[k,n] Y[k-n]}{\sum_{n=-N}^N W[k,n]} \quad (2)$$

This equation is simply a normalized weighted average of a neighborhood of $[2N+1]$ samples around the k th sample. The weight $W[k,n]$ are computed based on the content of the neighborhood. For the center sample $X[k]$, the weight $W[k,n]$ is computed by multiplying the following two factors [32]:

$$\begin{aligned}
 W_s[k, n] &= \exp\left\{-\frac{d^2\{[k], [k-n]\}}{2\sigma_s^2}\right\} = \exp\left\{-\frac{n^2}{2\sigma_s^2}\right\} \\
 W_r[k, n] &= \exp\left\{-\frac{d^2\{Y[k], Y[k-n]\}}{2\sigma_r^2}\right\} \\
 &= \exp\left\{-\frac{[Y[k] - Y[k-n]]^2}{2\sigma_r^2}\right\}
 \end{aligned} \quad (3)$$

The final weight is obtained by multiplying the above two factors

$$W[k, n] = W_s[k, n] \cdot W_r[k, n] \quad (4)$$

The weight includes two ingredients—the spatial and radiometric factors. The first factor measures the geometric distance between the center sample $[k]$ and the $[k-n]$ sample, and Euclidean metric is applied here. In this way, a neighbor sample closer to the center sample is assigned a larger weight. The second factor measures the radiometric distance between the values of the center sample $Y[k]$ and the $[k-n]$ sample, again, Euclidean metric is chosen. And also, the more similar is a neighbor sample to the center sample, it will be assigned a larger weight. As in Equation (3), the multiplication of the above two factors equals the addition of their exponential powers, which reveals the fact that the total distance formed by geometric and radiometric appears to be inversely proportional to the weight.

The bilateral filter is controlled by three parameters: N dictates the support of the filter. Larger support gives stronger smoothing. The parameters σ_s , σ_r control the decay of the two weight factors. For very large values, we get a simple uniform non-adaptive filtering, which is known to degrade the signal edges. Using too small values reduces the smoothing effect.

3.3. Wheeze Detecting Algorithm Based on 2D Bilateral Filtering of Spectrogram

The aim of the proposed algorithm is to be able to accurately detect and recognize all sorts of wheezing episodes (including harmonic wheezes, polyphonic wheezes, and also the inspiration spontaneous wheezes that belong to a type of wheezes of very low intensity) in any kind of respiratory sound recorded in wave files compliant with the CORSA standardized system.

The whole algorithm was implemented on a notebook using Matlab 6.5.1 (The Mathworks, Inc., Natick, MA). A schematic representation of the proposed algorithm is depicted in Fig. 3. Each procedure and their respective results when applied to an arbitrary segment of wheeze-with or wheeze-without sound are shown as follows:

(1) *Spectrogram*: Initially, each manually segmented respiratory sound file was loaded and some parameters regarding the length of the discrete Fourier transform, the type and length of time window, and overlapping percentage were defined. We used a discrete Fourier transform with a length of 4096 points to achieve an adequate frequency resolution of 5.38Hz/pixel. The Hanning window was used to obtain a rather smooth and acceptable spectrum leakage, and its length is about 23ms. The overlap of window was about 50%. The time scale interval in spectrogram was equal to 11.56ms, this gave an appropriate time resolution for wheezes. The resultant spectrogram can be viewed in Fig. 4 (a).

(2) *Limiter*: In order to isolate the high amplitude components, a limiter algorithm was developed. As different sounds can be recorded with different techniques, the resultant signal can present a variable recording level. To obtain the same limitation to any record level, the limiter algorithm calculated the mean value of the whole spectrogram, assigning a zero magnitude to all points which have values lower than the mean value of the spectrogram. After passing through the limiter, the wheeze episodes of spectrogram were more easily observed than in the original spectrogram, as shown in Fig. 4 (b).

(3) *Bilateral Filtering*: Bilateral filtering smoothes images while preserving edges, by means of a nonlinear combination of nearby image values. The method is noniterative, local, and simple. To reserve all the distinct lines that define the wheeze episodes in a spectrogram, a 2D bilateral filter was used to perform edge-preserving smoothing, which enhanced edges and reduced the noise. The processed image is shown in Fig. 4 (c).

(4) *Edge Detection*: This procedure used a Prewitt edge detector to recognize quasi-horizontal edges as contours. The resultant image is shown in Fig. 4 (d). The parameters used in a Prewitt edge detector are identical to those in a Sobel edge detector. The Prewitt edge detector is slightly simpler to implement computationally than the Sobel detector.

(5) *Image Closing, Image Opening, and Forming a Mask*: The morphological opening of A by B is using a simply erosion of A by B to get a result of the union of all translations of B that fit entirely within A . Opening is generally used to remove small objects from an image while preserving the shape and size of larger objects in the image. The morphological closing of A by B is also using a simply erosion of A by B to get a result of the complement of the union of all translations of B that do not overlap with A . Closing tends to smooth sections of contours but, as opposed to opening, closing fuses narrow breaks and long thin gulfs, eliminates small holes, and fills gaps in the contour. In this procedure, after image closing and

image opening were performed, the contours were filled while other unwanted stray lines were eliminated. The effects of image closing and opening are shown in Figs. 4(e) and 4(f). Eventually, there were quasi-horizontal lines in the spectrogram that formed a mask that roughly showed area and position of the wheeze episodes.

(6) *Keeping High and Isolated Amplitudes*: In previous studies, peak power in frequency bands are generically filtered by a fixed threshold. A fixed threshold chosen empirically may filter additional noise peak or not pass the necessary peaks of wheezes. In order to adapt a variable recording level, this procedure used different thresholds to assign a zero magnitude to individual points which have amplitudes lower than the percentage of $x_1, x_2, \dots, x_n$ of the highest values of spectrogram processed by two iterations of bilateral filtering. The concept of this procedure is shown in Fig. 5. The individual image then removed small and unacceptable objects in the spectrogram according to the following rules. Rule 1 is to preserve the blocks with widths (time duration) greater than 100ms, centroid greater than 150Hz, and heights (frequency) less than 200Hz. Rule 2 is to preserve the blocks with widths greater than 100ms, centroid greater than 150Hz, heights of boundary between 200Hz and 400Hz, and average heights less than 200Hz. Fig. 6 shows the blocks that complies with these rules. Eventually, all the image were added as a new image that only kept the quasi-horizontal lines and isolated objects, as shown in Fig. 4(g).

(7) *Filtered by the Mask*: The image consisting of high and isolated amplitudes has to pass through the mask generated by image opening and closing in step (5). The isolated objects that might have high power noise or interference could be removed via this mask. The result of this procedure is shown in Fig. 4 (h).

(8) *Recognition of Wheeze Episodes*: The final procedure applied the rules outlined in step (6) to recognize sounds as wheeze-with or wheeze-without. If the isolated objects conform to all these rules, the program will alarm the physicians that there are wheeze episodes in the spectrogram.

4. RESULT AND DISCUSSION

This proposed system, including respiratory sound capturing equipments and programs installed in the notebook, has been designed and implemented. The study was conducted on 30 volunteers including 15 asthmatic adults and 15 normal adults. The sounds were recorded in the some conditions, such as in a quiet environment, with the same sound capturing equipments, at the same location (at the trachea). All wave files were divided into 189 respiratory sound

Fig. 4. Resultant images obtained from: (a) Original spectrogram, (b) Spectrogram processed by the limiter, (c) Spectrogram processed twice by bilateral filtering, (d) Spectrogram processed by edge detection, (e) Image closing, (f) Image opening, (g) Spectrogram preserving high and isolated components, and (h) Spectrogram filtered by the mask.

Fig. 5. A mask generated by using different thresholds to assign a zero magnitude to individual points which have amplitudes lower than the percentage of $x_1, x_2, \dots, x_n$ of the highest values of spectrogram processed by two iterations of bilateral filtering.

cycles including 90 asthmatic respiratory sounds and 99 normal respiratory sounds. The asthmatic respiratory cycles might have all various kinds of wheeze episodes including wheeze with harmonics, polyphonic wheezes, and inspiration spontaneous wheezes, that helped verify the recognizing performance of our system in different cases.

Fig. 6. Two rules are used to remove small and unacceptable objects in the spectrogram image.

For validating the algorithm, the results obtained were compared with the auscultation performed by physicians. We chose a mask generated by a combination of different sections applied to assign a zero magnitude to individual points which have amplitudes lower than $x_1, x_2, \dots, x_n$ of the highest values of a spectrogram processed by using several different iterations of bilateral filtering. The estimated system performance (PER) is dependent on sensitivity (SE) and specificity (SP), that these are defined as the following formulas.

$$\text{Sensitivity}(SE) = \frac{\text{True Positive}(TP)}{\text{True Positive}(TP) + \text{False Negative}(FN)} \quad (5)$$

$$\text{Specificity}(SP) = \frac{\text{True Negative}(TN)}{\text{True Negative}(TN) + \text{False Positive}(FP)} \quad (6)$$

$$\text{Performance}(PER) = \sqrt{SE * SP} \quad (7)$$

For optimizing the algorithm, we measured the performance versus 6 different masks, and curves with iteration numbers ranging from 1 to 3 are shown in Fig. 7. Two factors affect the wheezing recognition of our proposed system. One factor is the iteration numbers of bilateral filtering. Too few iterations result in incomplete noise removal of spectrogram, and too many iterations generate blurred edges. Another factor is the mask generated by a combination of different sections responsible to assign a zero magnitude to individual points which have amplitudes lower than the variable percentage of the highest values of spectrogram processed by bilateral filtering. A mask consisting of more sections can find higher and more isolated amplitudes. However, a mask with too many sections may detect more high energy noise that causes the failure in non-wheezing detection.

From Fig. 7, we can see that using two iterations of bilateral filtering on Mask II can achieve an optimal solution. Although using Mask I can reach performance similar to Mask II, but Mask II needs fewer operations. Recognizing results with two iterations and Mask II are shown in Table II. The algorithm shows good distinctions between normal and wheezing respiratory records. In these offline computing processes, the spectrogram generation, filtering and limiting may spend about 8 seconds for a 10 seconds sound file on our notebook (Pentium4-M

Fig. 7. Performance versus different masks (iterations are from 1 to 3).

2.2GHz, 512MB RAM). This computation time is acceptable for offline analysis, but the algorithm needs improvement before it can be used in real-time recognition.

Table II. Results for separate respiratory cycle analysis

Recognition result	Specialist's diagnosis	
	Wheezing	Normal
Recognized as wheezing	TP=87	FP=8
Recognized as normal	FN=3	TN=91
Total	90	99

This proposed system has high sensitivity and high specificity in wheezing detection, but causes also some error detections. We will discuss the following issues related to the problems of error detection.

(1) Erroneous detection occurred by some interference from surroundings. The possible cause can be that the interference from AC power line may not be entirely clear, thus its appearance shows a constant edge at harmonics of 60Hz in spectrogram, which affects the detection of low pitch. Apparently, the problem also shows that the edges are close together. The solution is to add some noise reduction procedures and to strengthen the shielding.

(2) Polyphonic wheeze episodes with nearly aligned edge (pitches being too close) were detected as one single mass of wheeze episodes. The possible cause may be that some stray lines have been detected every time when Prewitt edge detector was applied after bilateral filtering. These stray lines affect the

correctness of image closing process, especially when wheezing edges have close pitches. The occurrence of stray lines may result from the incomplete reduction of noise after bilateral filtering, which seriously affects the performance of the noise-sensitive gradient operator based Prewitt edge detector. Some noise reduction procedures must be added to improve the overall performance.

(3) Wheeze episodes with high pitch deviation failed to be detected. The possible cause may be that the Prewitt edge detection was trying to prevent some erroneous detection in vertical edges generated from artifact. To reduce the effect, minimizing generation of non-respiratory sounds or using both vertical and horizontal edge detections will help.

5. CONCLUSION

A novel algorithm based on the 2D bilateral filtering of a spectrogram was developed to detect wheezes with high sensitivity. The system was subsequently validated by a medical doctor. The algorithm returns not only an automatic diagnostic but also processed data to the physicians. For this application, the treated spectrogram is shown on a computer screen before the automatic recognition. The result obtained during the experiments indicate that this algorithm can be quite useful in clinical diagnostics, mainly when the analysis can be made continually, using many respiratory cycles from patients. And high sensitivity and specificity were attained by the proposed wheeze detecting algorithm in qualitative analysis of wheezes without air flow data.

However, an improvement needs to be undertaken to get higher accuracy in detecting the duration of wheeze episodes. Some noise reduction procedures can be added between bilateral filtering and edge detection to improve the overall performance. And more subjects can be analyzed, using a more low-noise version of sound capturing system for sound recording.

The novel technique proposed in this study is a first step to analyze wheezing lung sounds. Due to its fast and simple features, it can be used to develop other advanced diagnosis systems, such as long-term wheezing monitoring for patients in sleep. Thus the method can be a useful tool for physicians studying pulmonary diseases.

REFERENCE

1. A. R. A. Sovijärvi, J. Vanderschoot, and J.E Earis, "Standardization of computerized respiratory sound analysis," *Eur. Respir. Rev.*, 2000; 77(10): 585-590.
2. A. R. A. Sovijärvi, L. P. Malmberg, G. Charbonneau, and J. Vanderschoot, "Characteristics of breath sounds and adventitious respiratory sounds," *Eur. Respir. Rev.*, 2000; 77(10): 591-596.
3. A. R. A. Sovijärvi, F. Dalmasso, J. Vanderschoot, L. P. Malmberg, G. Righini, and S. A. T. Stoneman, "Definition of terms for applications of respiratory sounds," *Eur. Respir. Rev.*, 2000; 77(10): 597-610.
4. T. R. Fenton, H. Pasterkamp, A. Tal, and V. Chernick, "Automated spectral characterization of wheezing in asthmatic children," *IEEE Trans. Biomed. Eng.*, 1985; 32(1) : 50-55.
5. G. R. Wodicka, K. N. Stevens, H. L. Golub, E. G. Cravalho, and D. C. Shannon, "A model of acoustic transmission in the respiratory system," *IEEE Trans. Biomed. Eng.*, 1989; 36(9): 925-934.
6. G. Charbonneau, E. Ademovic, B. M. G. Cheetham, L. P. Malmberg, J. Vanderschoot, and A. R. A. Sovijärvi, "Basic techniques of respiratory sound analysis," *Eur. Respir. Rev.*, 2000; 77(10): 625-635.
7. Y. Shabtai-Musih, J. B. Grotberg, and N. Gavriely, "Spectral content of forced expiratory wheezes during air, He, and SF₆ breathing in normal humans," *J. Appl. Physiol.*, 1992; 72: 629-635.
8. J. Xu, Q. Chen, Y. Zhang, and S. Liu, "Spectrum analysis of lung sounds," in *Proc. 11th IEEE/EMBS Int. Conf.*, Seattle, WA. USA, Nov. 9-11, 1989; 5: 1676-1677.
9. L. J. Hadjileontiadis, and S. M. Panas, "Nonlinear analysis of musical lung sounds using the bicoherence index," in *Proc. 19th IEEE/EMBS Int. Conf.*, Chicago, IL. USA, Oct. 30-Nov. 2, 1997; 3: 1126-1129.
10. R. Jané, D. Salvatella, J. A. Fiz, and J. Morera, "Spectral analysis of respiratory sounds to access bronchodilator effect in asthmatic patients," in *Proc. 20th IEEE/EMBS Int. Conf.*, Hong Kong, China, Oct. 29-Nov. 1, 1998 ; 6(6) : 3203-3206.
11. R. Jané, S. Cortés, J. A. Fiz, and J. Morera, "Analysis of wheezes in asthmatic patients during spontaneous respiration," in *Proc. 26th IEEE/EMBS Int. Conf.*, San Francisco, CA. USA, Sep. 1-5, 2004; 2: 3836-3839.
12. K. E. Forkheim, D. Scuse, and H. Pasterkamp, "A comparison of neural network models for wheeze detection", in *Proc. IEEE Commun., Power, and Computing Conf.*, Winnipeg, Man., 1995, May 15-16, 1995; 1: 214-219.
13. M. Bahoura, and C. Pelletier, "New Parameters for respiratory sound classification," in *Proc. IEEE Elect. and Computer Eng. Conf.*, Canada, May 4-7, 2003; 3: 1457-1460.
14. M. Bahoura, and C. Pelletier, "Respiratory sounds classification using Gaussian Mixture Models," in *Proc. IEEE Elect. and Computer Eng. Conf.*, Canada, May 2-5, 2004; 3: 1309-1312.
15. S. A. Taplidou, L. J. Hadjileontiadis, T. Penzel, V. Gross, and S. M. Panas, "WED: An efficient wheezing-episode detector based on breath sounds," in *Proc. 25th IEEE/EMBS Int. Conf.*, Cancun, Mexico, Sep. 17-21, 2003; 3: 2531-2534.
16. S. A. Taplidou, L. J. Hadjileontiadis, I. K. Kittsas, K. I. Panoulas, "On applying continuous wavelet transform in wheeze analysis," in *Proc. 26th IEEE/EMBS Int. Conf.*, San Francisco, CA. USA, Sep. 1-5, 2004; 2: 3832-3835.
17. A. Homs-Corbera, J. A. Fiz, J. Morera, and R. Jané, "Time-frequency detection and analysis of wheezes during forced exhalation," *IEEE Trans. Biomed. Eng.*, 2004; 51(1): 182-186.
18. M. Waris, P. Helistö, S. Haltsonen, A. Saarinen, and A. R. A. Sovijärvi, "A new method for automatic wheeze detection," *Technol. and Health Care*, 1998; 6(1): 33-40.
19. J. E. Earis, and B. M. G. Cheetham, "Current methods used for computerized respiratory sound analysis," *Eur. Respir. Rev.*, 2000; 77(10): 586-590.
20. L. Vannuccini, J. E. Earis, P. Helistö, B. M. G. Cheetham, and M. Rossi, A. R. A. Sovijärvi, and J. Vanderschoot, "Capturing and preprocessing of respiratory sounds," *Eur. Respir. Rev.*, 2000; 77(10): 616-620.
21. B. M. G. Cheetham, G. Charbonneau, A. Giordano, P. Helistö, and J. Vanderschoot, "digitization of data for respiratory sound recordings," *Eur. Respir. Rev.*, 2000; 77(10): 621-624.
22. P. Piirlä, A. R. A. Sovijärvi, J. E. Earis, M. Rossi, F. Dalmasso, S. A. T. Stoneman, and J. Vanderschoot, "Reporting results of respiratory sound analysis," *Eur. Respir. Rev.*, 2000; 77(10): 636-640.
23. D. Groom, "Standardization in phonocardiography: the microphone pickup," *Cardiology*, 1970; 55: 129-135.
24. A. Jones, D. Jones, K. Kwong, and S. SC, "Acoustic performance of three stethoscope chest pieces," in *Proc. 20th IEEE/EMBS Int. Conf.*, Hong Kong, China, Oct. 29-Nov. 1, 1998; 6(6): 3219-3222.

25. M. V. Scanlon, "Acoustically monitor physiology during sleep and activity," in Proc. 1st BMES/EMBS Conf., Atlanta, GA. USA, Oct. 13-16, 1999; 2: 787.
26. Z. Moussavi, "Vocal noise cancellation from respiratory sounds," in Proc. 23th IEEE/EMBS Int. Conf., Istanbul, Turkey, Oct. 25-28, 2001; 3: 2001-2003.
27. G. Jamieson, B. M. G. Cheetham, J. L. Moruzzi, and J. E. Earis, "Digital signal processing of lung sound," IEE Colloquium on DSP in Instrum. 1992; 9: 7/1-7/4, .
28. X. Q. Sun, B. M. G. Cheetham, K.G. Evans, and J. E. Earis, "Estimation of analogue pre-filtering characteristics for CORSA standardization," Technol. and Health Care, 1998; 6: 275-283.
29. C. Tomasi, and R. Manduchi, "Bilateral filtering for gray and color images," in Proc. 6th Int. Computer Vision Conf., Bombay, India, Jan. 4-7, 1998: 839-846.
30. M. Elad, "Analysis of the bilateral filter," in Proc. 36th Signals, Syst. and Comput. Conf., Nov. 3-6, 2002; 1: 483-487.
31. M. Elad, "On the origin of the bilateral filter and ways to improve it," IEEE Trans. Image Processing, 2002; 11(10): 1141-1151.
32. D. Barash, "A fundamental relationship between bilateral filtering, adaptive smoothing, and the nonlinear diffusion equation," IEEE Trans. Pattern Anal. Machine Intell., 2002; 24(6): 844-847.