ISSN 2229-5518

A Method for Detecting Transient Respiratory Disturbances Using Quadratic Transformations

Azeemsha Thacham Poyil, Hedi Khammari

Abstract— The paper suggests an improved method for diagnosing of transient respiratory disturbances by analyzing the respiratory signals using quadratic time-frequency transformation techniques. Wigner Ville Distribution (WVD) is a good method for analyzing non-stationary signals since it gives a good time-frequency resolution compared to many other time-frequency representations. The time marginal of Wigner Ville Distribution can be used for detecting the presence of transient and non-stationary signals. In this work, a cross-term reduced WVD was used for detecting abnormal respiratory disturbances. An adaptive-kernel based ambiguity domain filtering was used to remove the cross-terms in Wigner Ville Distribution. Transient detection algorithms were implemented using cross-term reduced Wigner Ville Distribution and the results were compared with that of Short Time Fourier Transform based methods. The respiratory signals are collected from 5 different test subjects using National Instruments data acquisition devices. The collected signals were then passed through the detection algorithms for testing the performance of the methods. The results from the experiments suggest that the improved Wigner Ville Distribution could be used to detect the transient respiratory disturbances in a better way as compared to the algorithms using STFT, and this can be used in diagnosis of respiratory disturbances.

Index Terms— Transient Respiratory Disturbances, Instantaneous Power, Wigner Ville Distribution, Short Time Fourier Transform, Ambiguity Function, Biomedical Signal Processing, Quadratic Transformations

1 INTRODUCTION

THE respiratory disturbances which are transient in nature can be analyzed using various signal processing methods. Quadratic transformation like Wigner Ville Distribution is a very good method for analyzing the time-frequency resolution of non-stationary signals and also for the detection of transients. The time marginal properties of WVD can be used for the detection and analysis of abnormal transient behavior of the human respiratory system. The mathematical cross-terms in WVD can be reduced by performing suitable filtering in its Ambiguity Function (AF) domain, so that the performance of transient detection algorithm can be improved. Much previous research has investigated different time-frequency-scale techniques in various biomedical signal processing applications. It has been shown that time-frequency analysis is an effective tool for analysis non-stationary signals. Few have tried to research the methods for diagnosis of respiratory diseases in either time or spectral domain. These researches are not found utilizing the properties of WVD transformations in the respiratory signal analysis and detection of transient respiratory disturbances. This research paper presents the use of an improved version of WVD and its time marginal property for the detection of transient respiratory disturbances in order to help in the diagnosis of respiratory diseases.

The rest of the paper is organized as follows. The related works are briefly reviewed in section 2. Then section 3 presents an overview of the scientific background behind the work and the different transformation techniques used in the past for time-frequency analysis. The section 4 describes the experimental setup and the protocol used in this research. The results and discussion about the results are presented in section 5, and we conclude the paper in section 6

2 LITERATURE REVIEW

In recent years, there have been several studies contributed by different groups in the area of time-frequency transformations and respiratory signal analysis. One of these dealt with asynchronous breathing movements in patients with chronic obstructive pulmonary disease [1]. The study concentrated on the anterior-posterior movements of the chest and abdomen during the breathing cycle in 30 patients with chronic obstructive pulmonary disease and in 10 normal subjects. However the researches did not use any time-frequency analysis tools and transformations during these studies. In another study, Drummond and team investigated thoracic impedance used for measuring chest wall movement in postoperative patients [2]. Thoracic impedance and rib cage band signals were collected from 10 patients after abdominal surgery and studied. The study was purely in the time domain and no spectral analysis was conducted. In the work by Joonas Paalasmaa et al, the structure of sleep was studied in time domain by measuring the variation of the respiratory rate [3]. A new method was introduced to extract the variation in respiratory rates through indirect measurements of respiration, which is particularly suitable for force sensor signals. Thacham Poyil and team investigated time-frequency analysis of signals using Wigner Ville Distribution and variants that can be used in the detection and analysis of non-stationary signals [4]. Ayappa et al worked on non-invasive detection of apnea and hypopnea in 15 subjects by a nasal cannula/pressure transducer system and the analysis was not targeted for a spectral or time-

- *Author Azeemsha Thacham Poyil is currently a research scholar and has done his masters degree in electronics from Cochin University of Science and Technology, India. E-mail: azeemsha.tp@gmail.com*
- *Co-Author Hedi Khammari is currently working as Associate Professor in the Department of Computer Engineering, College of Computers and IT, Taif University, Saudi Arabia. E-mail: gham.hedi@hotmail.com*

ISSN 2229-5518

frequency domain [5]. A study by George et al researched on predicting the effects of air cavity depth of electret microphones when used for measuring lung sounds [6]. It was found that the overall high-frequency response of the transduction diminishes with increasing cavity depth. The study was not concentrated on the methods used for the respiratory signal analysis, instead was focusing on the device used for capturing the signals. Similarly, Foad Ghaderi et al. [7] described localizing heart sounds in respiratory signals using spectrum analysis techniques. The focus was on methods for the cancellation of heart sounds from respiratory sound signals. The study was done using time series analysis techniques like singular spectrum analysis (SSA), but no time-frequency transformation techniques were experimented here.
A research describes about the analysis of respiratory auscultation sounds using various techniques. Spectral density and amplitude of sound signals are studied using Spectrogram plots and automatic detection tools were developed [8]. A better transformation like WVD could also be tried here in place of the Spectrogram techniques. Another research work described the modelling of the human respiratory system using Impulse Oscillometry data [9]. A different work by M. T. Pourazad and team explored some techniques for heart sound cancellation from lung sound recordings using time-frequency filtering by multi-resolution decomposition of the wavelet transform coefficients [10]. In a work by Homs-Corbera et al proposed a method to detect and analyse wheezes during forced exhalation by means of a highly sensitive time-frequency algorithm [11]. A study of computer-based respiratory sound analysis was conducted by Rajkumar Palaniappan et al [12]. A comprehensive review on computer‐based respiratory sound analysis techniques was done. Computer‐based methods were suggested as powerful tools for diagnosing abnormalities and disorders in the lung. In a similar study, a systematic review was conducted on computerized lung sound analysis techniques which were used as diagnostic aid for the detection of abnormal lung sounds [13]. The results showed that much of the research used either electret microphones or piezoelectric sensors for auscultation, and Fourier Transform and Neural Network Algorithms for analysis and automated classification of lung sounds. Another work in this area concentrated on the classification of wheeze sounds using wavelets and neural networks [14]. The wheeze sounds were classified with an accuracy of 89.28 percent. A team of researchers in the Dept of Clinical Physiology and Nuclear Medicine, Helsinki University Hospital developed many guidelines for research and clinical practice in the field of respiratory sound analysis. In brief, the research works included different topics like current methods used for computerized respiratory sound analysis, characteristics of breath sounds and adventitious respiratory sounds, definition of terms for applications of respiratory sounds, capturing and preprocessing of respiratory sounds, digitization of data for respiratory sound recordings, basic techniques for respiratory sound analysis, reporting results of respiratory sound analysis and future perspectives for respiratory sound research [15]. A method for cross-term reduction in Wigner Ville Distribution using Wigner Hough Transform was discussed in [16], but the applications of this method in respiratory signal analysis was not covered. Another work by Hedi Khammari explored the prediction of sudden cardiac arrest using time-frequency analysis tools [17].
It can be seen that much of the past research tried to study and address the issues in using the time-frequency-scale techniques (like STFT, Wavelet Transforms and WVD variants) in various applications. And many others tried to research on the methods for diagnosis of respiratory diseases in time or spectral domain. Despite the vast research efforts on the cross-term reduction algorithms for WVD, further study is still required to apply these results in to the diagnosis of diseases. It is noticed that none of the above researches were trying to utilize the useful properties of WVD transformations in the respiratory signal analysis and detection of transient respiratory disturbances. Our study in this paper tries to make some contributions to this problem. Future work in this direction will try to improve the algorithms by better cross-term cancellation techniques and different variant transformations.

3 Scientific Background

In this section, we explain the scientific background behind the research for reducing the cross-terms in Wigner Ville Distribution and for detection of respiratory transients.

3.1 Reducing Cross-Terms in WVD

The inverse Fourier transform of the Wigner-Ville distribution is called the ambiguity function (AF). On applying Fourier transform on the Wigner-Ville distribution of signals, the auto-terms will be mapped to a region in the center of the AF domain. The oscillating cross-terms are mapped away from the origin of AF plane. So the auto-terms and cross-terms are separated in the AF domain. If we can apply a suitable filter function to the WVD in the plane of Ambiguity function, we can suppress some of the cross-terms based on the effectiveness of the filter function. This filtering operation results in the below time-frequency distribution,

$$\text{TFR} = \text{Fourier transform } \{\text{Ambiguity Function} \cdot \text{Kernel}\} \quad (1)$$

The properties of this TFR are different from the Wigner-Ville distribution. The filter function is called the 'kernel' of the TFR. Since there are many possible 2-dimensional kernel functions possible, there are many different TFRs for the same signal [4], [17].
Ambiguity function of any signal x, gives a measurement of the time-frequency correlation of the signal, i.e.it measures the similarity between the signal x(t) and its translated versions in the time-frequency plane. It can be expressed as

$$A_x(\xi, \tau) = \int_{-\infty}^{+\infty} x(s + \tau/2).\, x^*(s - \tau/2)\, e^{-j2\pi\xi s}\, .ds \quad (2)$$

The variables 't' and 'ν' are the "absolute" time and frequency coordinates and, the variables 'τ' and 'ξ' are "relative" delay and Doppler coordinates respectively.

ISSN 2229-5518

3.2 Detection of Transient Signals

All tables and figures will be processed as images. You need to embed the images in the paper itself. Please don't send the images as separate files.

Transient signals are usually non-stationary signals where the time of arrival of the signal cannot be known in advance and their duration will be very small in comparison to the analysis interval. Even though the detection and analysis of transient signals can be done by using STFT or Wavelet Transform, there is a limitation in those methods. Since the signal occurrence time is not known, it is not possible to determine and use a window function in an optimal way. This results in a bad performance in the detection of transients. To achieve a better performance for the detection of such signals, the parameter for detection of such signals must be invariant to the signal duration. When the time duration of the transient signal changes, this corresponds to a change in the total energy of the signal. This means that the magnitude of the peak of the signal in its frequency spectrum will be affected. So, if the pulse width of the transient signal is reduced, there will be a corresponding decrease in magnitude of the peaks of TFRs, at that particular frequency and time. Hence we are going for a different property of WVD distribution which helps us to improve the performance degradation in the transient detection [4], [17]. The WVD of the received signal can be used to get an estimate of the instantaneous signal power. So we are trying to make use of the time-marginal property of WVD to calculate the instantaneous signal power, which do not depend on the signal time duration. The time marginal property of WVD is defined as,

$$\int_{-\infty}^{+\infty} W_s(t,\nu)d\nu = |s(t)|^2 \tag{3}$$

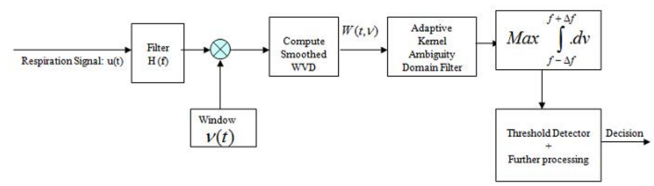
From the equation, it is clear that, the instantaneous signal power is obtained by integrating WVD over the frequency. And the resultant quantity $|s(t)|^2$ does not depend on the time duration of the signal. It only represents the amplitude of the analysis signal. So the instantaneous signal power calculated from the WVD of the signal is the parameter used for transient signal detection in this paper. An equivalent equation for the Spectrogram gives the average signal energy over the duration of the window w(t) as shown below.

$$\int_{-\infty}^{+\infty} S_s(t,\nu)d\nu = \int_{-\infty}^{+\infty} |s(\tau)|^2 |w(\tau-t)|^2 d\tau \tag{4}$$

This helps us to conclude that the time marginal of Spectrogram is very much dependent on the duration of the analysis signal, because there is a time window associated. This results in a reduced performance of Spectrogram when used for detection comparison with WVD.

4 Experimental Setup

The experimental setup for detection of transient respiratory disturbances is shown in (Figure 1) [4], [16]. The signal u(t) is the input respiratory signal collected by suitable sensors and data acquisition devices. The Smoothed Wigner Ville Distribution (WVD) of the signal is computed after choosing a suitable window. As described before, this will contain both auto-terms and cross-terms. In order to filter out the cross-terms from WVD the Ambiguity Function will be calculated and plotted. In the Ambiguity Function (AF) plane, the cross-terms are positioned away from the origin. To do this filtering, a kernel is designed that adapts its shape to the signal properties. After filtering out the cross-terms in the AF plane, we now have the terms that correspond to the auto-terms in majority. By performing the inverse of the AF, the algorithm brings back to the WVD domain with a majority of auto-terms. Now the time marginal of the WVD is calculated by integrating the resultant WVD (after removing the cross-terms) along the frequency axis, and the peak value of the integration result is noted. This value represents the peak instantaneous power parameter that can be used for detecting the presence transients in a respiratory signal. The non-stationary transient signals present in a respiratory/chest signals can be accurately detected by this algorithm.



Hardware Connection for Data Acquisition Device

Respiration Sensor

Sensor Isolator

Figure 1: Experiment Setup for Transient Signal Detection using Modified WVD

4.1 Protocol for Data Acquisition

The inverse Fourier transform of the Wigner-Ville distribution is called the ambiguity function (AF). On applying Fourier transform on the

1) The DAQ device is connected with the respiratory sensors and the power sources are connected accordingly
2) The respiration sensor belt is connected to upper diaphragm region of the test subject
3) The subjects are asked to sit on a chair be in a relaxed position
4) The subjects are asked to take normal breaths
5) A LabVIEW application is run on the computer to collect the signals to the computers. The application reads the

ISSN 2229-5518

respiratory sensor values from the data acquisition device.

6) 6 trials each of 1 minute duration are taken from all the 5 different subjects. A sampling frequency of 1000 samples/second is used so as to capture a high frequency transient.

4.2 DAQ Equipment and Sensors

The equipment that was used for the acquisition of respiratory signals from different test subjects include NI Compact DAQ chassis and Accessories (NI cDAQ-9174), Isolated Analog Input Module (NI 9239) are shown in Figure 1. The setup consists of data acquisition devices from National Instruments and the respiratory sensors from Thought Technology connected together. The output of the DAQ hardware is connected to a PC which installed with LabVIEW. The DAQ device communicates with the Computer through a USB port. The respiration signal is a relative measure of abdomen expansion. The Respiration Sensor is a sensitive girth sensor using an easy fitting high durability latex rubber band fixed with self-adhering belt. It detects chest or abdominal expansion/contraction and shows the respiration waveform and amplitude. It can be worn over clothing.

5 Results & Discussion

Applying the WVD and STFT transformations and further algorithms based on ambiguity-domain filtering and transient detection, we obtained a set of results which help in describing the performance of different distributions for detection of transient respiratory disturbances.

As a pilot study, the WVD representation of 2 Linear FM signals with an added random noise and the ambiguity function was measured and plotted. We could see that the cross-terms were distributed away from the centre of the AF. A signal dependent adaptive kernel based on Gaussian function was applied to filter out the 'away' components in the Ambiguity function. The kernel was multiplied with the ambiguity function in order to create the new ambiguity function having reduced cross-terms. Now the inverse FFT on this filtered ambiguity function gave rise to the modified WVD with reduced cross-terms [4], [16].

The respiratory signals collected using the data acquisition device from different subjects are analysed. The algorithm for detecting any possible transient respiratory disturbances is tested. The test is conducted on 5 different subjects of similar age groups. Two of them were having mild respiratory disturbances and unusual yawning frequencies.

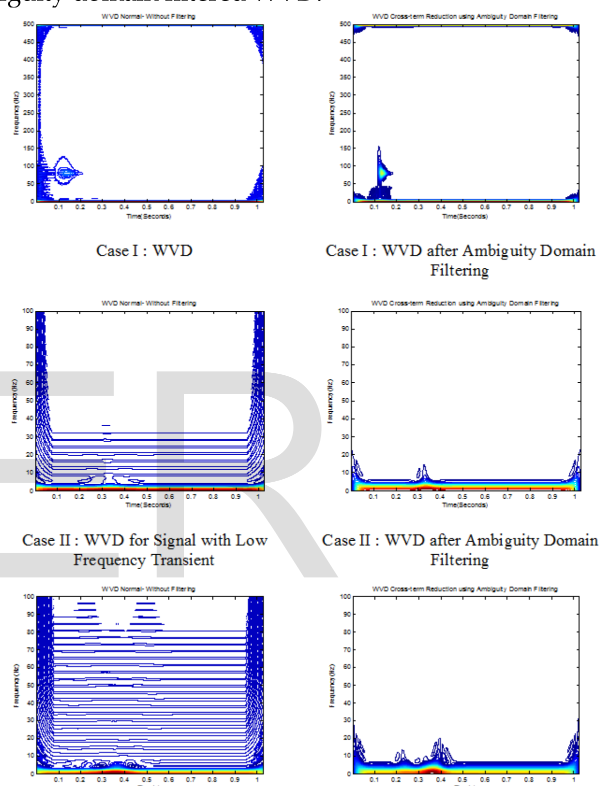
5.1 WVD after Ambiguity Domain Filtering

The Wigner Ville Distribution is calculated and plotted for the respiratory signals from different subjects in Figure 2.

Case I: The WVD of a respiratory signal in presence of a relatively high frequency transient signal is shown in the first image. The WVD domain shows the original respiratory signals almost along the x-axis at very low frequencies. The Transient signal is shown in a triangular shape at a frequency range of 75Hz. The signal components in plot other than the transient signal and the respiratory signal are the cross-terms of WVD. The second image shows the WVD after undergoing the ambiguity domain filtering using adaptive kernel. It can be clearly noticed that the cross-terms of WVD are considerably reduced here.

Case II: The second row images of Figure 2 shows signal with a low frequency transient before and after ambiguity domain filtering. Here also the reduction in the number of cross-terms after the ambiguity domain filtering can be clearly noticed. The transient signal in the range of nearly 10Hz is found to be closer to the respiratory signal in comparison to the previous case.

Case III: A similar analysis of the respiratory signals with multiple transients is shown in the third row images of Figure 2. It can be noticed that the number of cross-terms are lesser in the ambiguity domain filtered WVD.



Case I : WVD

Case I : WVD after Ambiguity Domain Filtering

Case II : WVD for Signal with Low Frequency Transient

Case II : WVD after Ambiguity Domain Filtering

Case III: WVD for Signal with Multiple Transients

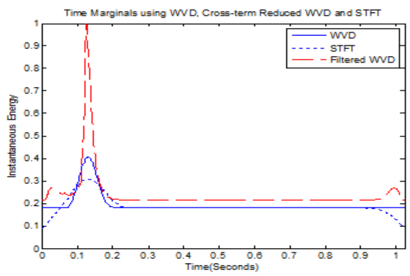
Case III: WVD after Ambiguity Domain Filtering

Figure 2: WVD of signal in different cases before and after Ambiguity Domain Filtering

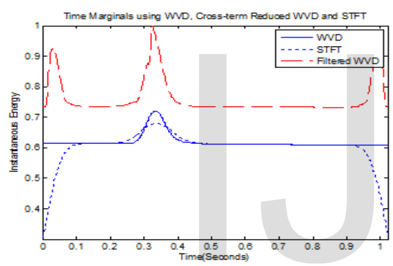
5.2 Detection of Transients in the Respiratory Signals

The time marginal property of WVD is used for detecting the presence of transients in the respiratory signal quantitatively and the results are plotted in Figure 3. In case I, the experiment with a high frequency transient in the respiratory signal produced a result as in the first image. The values of the instantaneous energy are calculated using the time marginal of STFT, WVD and cross-term reduced WVD. The instantaneous energy using all these methods is plotted and peak values are noted down. As can be seen in the figure, the peak instantaneous energy for the same signal is found to be highest in the cross-term reduced WVD and the lowest in the STFT plots. This states that the cross-term reduced WVD using ambiguity domain filtering has improved the performance of transient detection in the respiratory signals. In case II, a similar experiment with a lower frequency transient in the respiratory signal produced a result as in the second image. In case III, the experiment with multiple numbers of transients in the respiratory signal gave rise to plot as given in the third image.

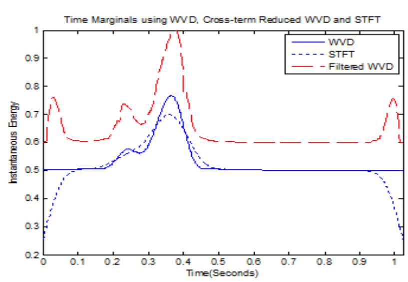
All these results confirm the fact that the WVD after ambiguity domain filtering using an adaptive kernel results in a better detection of transients in a respiratory signal. The peak value of the instantaneous energy in the filtered WVD is found to be higher in all cases.



Case I



Case II



Case III

Figure 3: Time marginal of WVD and STFT in different cases

6 Conclusions

The above experiments and results prove how the ambiguity domain filtering helps in reducing cross terms in WVD, and how this can help in detecting the presence of disturbances in respiratory signals and thus in the diagnosis of respiratory diseases. The respiratory signals were collected using suitable data acquisition devices. The signals were then used to test the transient detection algorithm and the results were compared between STFT, WVD and cross-term reduced WVD. Through the experiments we find that the time marginal of the cross-term reduced variant of WVD, while used for the detecting transient respiratory disturbances gives a better performance in comparison with the previous methods using STFT and Smoothed WVD. We believe that there is still possibilities for improvements in the above algorithm by further reducing the cross-terms in WVD through different filtering mechanisms.

Acknowledgement

Authors express gratitude and appreciation to King Abdulaziz City for Science and Technology, Saudi Arabia for providing the resources for the research (Project No: PC 12-32). Authors would also like to express thanks to Taif University, Saudi Arabia where the research was carried out, and to any individual or entity that had provided help and assistance during the course of this project.

References

[1] Kumar Ashutosh, M.D, Robert Gilbert, M.D. J. H. Auchincloss, Jr. M.D, S and David Peppi (1975), Asynchronous Breathing Movements in Patients with Chronic Obstructive Pulmonary Disease, CHEST, 67: 5, (http://journal.publications.chestnet.org/ 09/11/2014)

[2] Drummond GB, Nimmo AF, Elton RA (1996). Thoracic impedance used for measuring chest wall movement in postoperative patients, British Journal of Anaesthesia 1996;77:327–332

[3] Joonas Paalasmaa, Lasse Leppäkorpi, and Markku Partinen (2011), Quantifying Respiratory Variation with Force Sensor Measurements Engineering in Medicine and Biology Society,EMBC, 2011 Annual International Conference of the IEEE, Boston, MA, Aug. 30 2011-Sept. 3 2011

[4] Azeemsha Thacham Poyil, Sulthan Aljahdali, Nasimudeen KM (2013), Significance of Cohen's Class for Time Frequency Analysis of Signals, International Journal of Computer Applications (IJCA), Vol. 72(12):1-8

[5] Indu Ayappa PhD, Robert G Norman MS, Ana C Krieger MD, Alison Rosen MA, RPsgT, Rebecca L O'Malley, and David M Rapoport MD (2000), Non-Invasive Detection of Respiratory Effort-Related Arousals (RERAs) by a Nasal Cannula/Pressure Transducer System, SLEEP, Vol. 23, No. 6

[6] George R. Wodicka; Steve S. Kraman; Gerald M. Zenk; Hans Pasterkamp (1994), Measurement of Respiratory Acoustic Signals: Effect of Microphone Air Cavity Depth, Chest. 1994;106(4):1140-1144. doi:10.1378/chest.106.4.1140

[7] Foad Ghaderi, Hamid R. Mohseni, and Saeid Sanei (2011), Localizing Heart Sounds in Respiratory Signals Using Singular Spectrum Analysis, IEEE Transactions On Biomedical Engineering, Vol. 58, No. 12

[8] Sandra Reichert, Raymond Gass, Christian Brandt and Emmanuel Andrès (2008), Analysis of Respiratory Sounds: State of the Art, Clinical Medicine: Circulatory, Respiratory and Pulmonary Medicine 2008:2 45–58

[9] Bill Diong, Homayoun Nazeran, Patricia Nava, And Michael Goldman (2007), Modeling Human Respiratory Impedance, IEEE Engineering In Medicine And Biology Magazine

[10] Pourazad, M.T., Mousavi, Z.K., Thomas, G (2003), Heart sound cancellation from lung sound recordings using adaptive threshold and 2D interpolation in time-frequency domain, Engineering in Medicine and Biology Society, 2003. Proceedings of the 25th Annual Interna-

tional Conference of the IEEE (Volume:3), 17-21
[11] Homs-Corbera, A. Fiz, J.A. Morera, J. Jane, R (2004), Time-frequency detection and analysis of wheezes during forced exhalation, IEEE Transactions on Biomedical Engineering, Page 182 - 186
[12] Rajkumar Palaniappan, Kenneth Sundaraj, Nizam Uddin Ahamed, Agilan Arjunan and Sebastian Sundaraj (2013), Computer-based Respiratory Sound Analysis: A Systematic Review, IETE Technical Review,Vol 30, Issue 3
[13] Arati Gurung, Carolyn G Scrafford, James M Tielsch, Orin S Levine, and William Checkley (2011), Computerized Lung Sound Analysis as diagnostic aid for the detection of abnormal lung sounds: a systematic review and meta-analysis, Respir Med. 105(9): 1396–1403
[14] Amjad Hashemi, Hossein Arabalibiek, Khosrow Agin (2011), Classification of Wheeze Sounds Using Wavelets and Neural Networks, 2011 International Conference on Biomedical Engineering and Technology, IPCBEE vol.11
[15] A.R.A. Sovijärvi, J. Vanderschoot, J.E. Earis (2000), Standardization of computerized respiratory sound analysis, European Respiratory Review 2000; 10: 77, 585
[16] Azeemsha Thacham Poyil, Shadiya Alingal Meethal (2012), Cross-term Reduction Using Wigner Hough Transform and Back Estimation, ICICEE2012: 2012 International Conference on Industrial Control and Electronics Engineering, IEEE Computer Society Washington, DC, USA Issue date 23-25
[17] Hedi Khammari (2012), A New Spectral Based Characterization of Electrocardiogram Signals in Sudden Cardiac Death. IJCSI International Journal of Computer Science Issues. 9(2)