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**REAL-TIME VIRTUAL PATHOLOGY USING SIGNAL ANALYSIS AND
SYNTHESIS**

by

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A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPHY

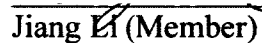
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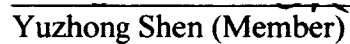
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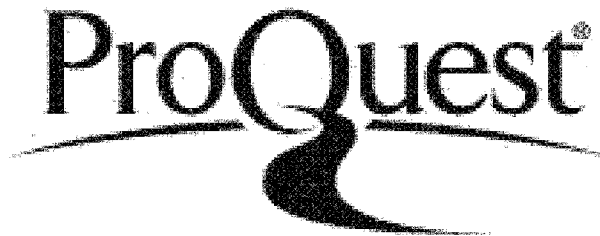


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ABSTRACT

REAL-TIME VIRTUAL PATHOLOGY USING SIGNAL ANALYSIS AND SYNTHESIS

Dennis L. Bergin
Old Dominion University, 2012
Director: Frederic D. McKenzie

This dissertation discusses the modeling and simulation (M&S) research in the area of real-time virtual pathology using signal analysis and synthesis. The goal of this research is to contribute to the research in the M&S area of generating simulated outputs of medical diagnostics tools to supplement training of medical students with human patient role players.

To become clinically competent physicians, medical students must become skilled in the areas of doctor-patient communication, eliciting the patient's history, and performing the physical exam. The use of Standardized Patients (SPs), individuals trained to realistically portray patients, has become common practice. SPs provide the medical student with a means to learn in a safe, realistic setting, while providing a way to reliably test students' clinical skills. The range of clinical problems an SP can portray, however, is limited. SPs are usually healthy individuals with few or no abnormal physical findings. Some SPs have been trained to simulate physical abnormalities, such as breathing through one lung, voluntarily and increasing blood pressure. But, there are many abnormalities that SPs cannot simulate.

The research encompassed developing methods and algorithms to be incorporated into the previous work of McKenzie, *et al.* [1]–[3] for simulating abnormal heart sounds in a Standardized Patient (SP), which may be utilized in a modified electronic stethoscope. The methods and algorithms are specific to the real-time modeling of human body sounds through modifying the sounds from a real person with various abnormalities. The main focus of the research involved applying methods from tempo and beat analysis of acoustic musical signals for heart signal analysis, specifically in detecting the heart rate and heartbeat locations. In addition, the research included an investigation and selection of an adaptive noise cancellation filtering method to separate

heart sounds from lung sounds.

A model was developed to use a heart/lung sound signal as input to efficiently and accurately separate heart sound and lung sound signals, characterize the heart sound signal when appropriate, replace the heart or lung sound signal with a reference pathology signal containing an abnormality such as a crackle or murmur, and then recombine the original heart or lung sound signal with the modified pathology signal for presentation to the student. After completion of the development of the model, the model was validated. The validation included both a qualitative assessment and a quantitative assessment. The qualitative assessment drew on the visual and auditory analysis of SMEs, and the quantitative assessment utilized simulated data to verify key portions of the model.

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This thesis is dedicated to the memory of my mother in-law and father in-law, Annabel and Russell Kerlin. Annabel was an amazing woman: a loving wife, mother, and grandmother. Russell was an extraordinary man: a loving husband, father and grandfather. Both Russell and Annabel were amazing educators for more than 30 years. They both taught my wife, my children and myself so much about life, selfless love, the true meaning of family and education. I am blessed to have had them both in my life. They are both true angels of God and my heroes!

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NOMENCLATURE

<i>ANC</i>	Adaptive Noise Cancellation
<i>AR</i>	Autoregressive
<i>BPM</i>	Beats Per Minute
<i>CPU</i>	Central Processing Unit
<i>DB</i>	Decibels
<i>EVMS</i>	Eastern Virginia Medical School
<i>FFT</i>	Fast Fourier Transform
<i>FIR</i>	Finite Impulse Response
<i>FOS</i>	Fourth Order Statistics
<i>HS</i>	Heart Sound
<i>HZ</i>	Hertz
<i>IFFT</i>	Inverse Fast Fourier Transform
<i>IIR</i>	Infinite Impulse Response
<i>LMS</i>	Least Mean Squares,
<i>LSM</i>	Least Square Mean
<i>LHR</i>	Lung Sound to Heart Sound Ratio
<i>LS</i>	Lung Sound
<i>MA</i>	Moving Average
<i>MSE</i>	Mean Square Error
<i>MIDA</i>	Medical Imaging Diagnosis and Analysis
<i>M&S</i>	Modeling and Simulation
<i>OSCE</i>	Observed Structured Clinical Examination
<i>RLS</i>	Recursive Least Squares
<i>RMS</i>	Root Mean Square
<i>SME</i>	Subject Matter Expert
<i>SP</i>	Standardized Patient
<i>WAV</i>	Waveform Audio File Format
<i>WT</i>	Wavelet Transform

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CHAPTER 1

INTRODUCTION

This dissertation discusses the modeling and simulation (M&S) research in the area of real-time virtual pathology using signal analysis and modification. The goal of this research is to contribute to the research in the M&S area of generating simulated outputs of medical diagnostics tools to supplement training of medical students with human patient role players. The research encompassed developing methods and algorithms to be incorporated into the previous work of McKenzie, *et al.* [1]–[3] for simulating abnormal heart sounds in a Standardized Patient (SP), which may be utilized in a modified electronic stethoscope. The methods and algorithms are specific to the real-time modeling of human body sounds through modifying the sounds from a real person with various abnormalities. The main focus of the research involved applying methods from tempo and beat analysis of acoustic musical signals for heart signal analysis, specifically in detecting the heart rate and heartbeat locations. In addition, the research included an investigation and selection of an adaptive noise cancellation filtering method to separate heart sounds from lungs sounds.

1.1 Motivation

The physical examination of patients is integral to family practice, with cardiac auscultation playing a particularly important part. If performed well, assessment of cardiac pathology via auscultation correlates highly with the results of echocardiography or angiography at a fraction of the cost and with no risk to the patient. Cardiac auscultation allows for physical contact between patient and physician, which forms a

bond that cannot be replicated with diagnostic machinery. For these reasons, medical educators have placed significant emphasis on the value and clinical importance of cardiac auscultation.

To become clinically competent physicians, medical students must become skilled in the areas of doctor-patient communication, eliciting the history, and performing the physical exam. These skills are emphasized in the medical student's early clinical training. The use of Standardized Patients (SPs), individuals trained to realistically portray patients, has become common practice to teach and assess medical students in these areas. SPs provide the medical student with a means to learn doctor-patient communication, the history, the physical exam, and other clinical skills in a safe, realistic setting, while providing a way to reliably test students' clinical skills. The range of clinical problems an SP can portray, however, is limited. SPs are usually healthy individuals with few or no abnormal physical findings. Some SPs have been trained to simulate physical abnormalities, such as breathing through one lung, voluntarily and increasing blood pressure. But, there are many abnormalities that SPs cannot simulate. In the past, it was thought that augmenting SPs with the ability to simulate abnormal physical findings would expand the opportunities for students to learn more and better clinical skills in a realistic setting with a live person, while practicing their doctor-patient communication skills.

The practical benefits of this M&S research will work to further advance training related technology in the medical field, specifically to supplement training of medical students with human patient role players. Since there are many abnormalities that SPs cannot simulate, it is anticipated that augmenting SPs with the ability to simulate

abnormal physical findings will expand the opportunities for students to learn more and better clinical skills in a realistic setting with a live person, while practicing their doctor-patient communication skills.

1.2 Influence on Modeling and Simulation Discipline

Along with providing practical benefits to the medical field, this research can influence the discipline of modeling & simulation. In particular, the novelty of the research is in efficiently applying musical tempo and beat analysis algorithms to pathological sound signals in order to perform various signal analyses for modeling human body sounds in real-time. This study contributes to the exploding area of medical modeling and simulation. The constraints of efficiency, memory, and interfacing are dictated by the real-time nature of the intended application. The development of an accurate and efficient model provides modeling and simulation technology in the challenging environment of real-time medical applications.

1.3 Thesis Statement

To facilitate the training of medical students in auscultation, methods from tempo and beat analysis of acoustic musical signals can be applied to heart signal analysis to detect the heart rate and heartbeat locations in an efficient manner applicable to a real-time heart and lung sound signal modification.

McKenzie, *et al.* in the area of augmented SPs have completed a great deal of work [1]–[3]. It has been identified that the identification of plausible signal modification systems would require further work in both heart and lung sound analysis, and heart

sound signal modification techniques to better define the requirements for the system. Therefore, the main objectives of the research were to 1) determine an optimum technique of separating heart sounds from lung sounds from the fifteen techniques reviewed by Gnitecki and Moussavi [4] for the specific application of modifying the separated components and recreating a realistic signal. 2) To investigate and prove the plausibility of applying the acoustic music signal tempo and beat detection algorithms of Scheirer [5] to heart rate detection and heartbeat localization. Efficient and optimum techniques are defined as techniques that are conducive to supporting real-time pathology signal analysis and modification.

1.4 Description of the Problem

It would be very beneficial to present an augmented SP with various abnormalities in a real-time and realistic setting to the practicing doctor. The research by McKenzie, *et al.* [1]–[3] has involved simulating abnormal heart or lung sounds in an SP to expand the breadth of sounds that can be heard by the medical student. The work of McKenzie, *et al.* [1]–[3] was successful in using a modified stethoscope combined with augmented SPs to increase the range of heart and lung abnormalities. While the previous work was successful in combining simulated crackles into real SP breath sounds, the system was not fully automated. The SP still had to signal the end of his/her inspiration to trigger the insertion of a pre-processed signal containing a heart abnormality. This is an example of the limitations in the capabilities provided by SPs with regards to realistic scenarios. Overcoming this specific limitation is the focus of this dissertation.

1.5 Proposed Solution

The research referenced in this dissertation focused on developing methods and algorithms to extend the previous work of McKenzie, *et al.* [1]–[3] for simulating abnormal heart sounds in a Standardized Patient (SP), which may be utilized in a modified electronic stethoscope. The methods and algorithms are specific to the real-time modeling of human body sounds through modifying the sounds from a real person with various abnormalities. The research involved applying methods from tempo and beat analysis of acoustic musical signals for heart signal analysis, specifically in detecting the heart rate and heartbeat locations.

To further the work of McKenzie, *et al* [1]–[3] in the area of augmented SPs, a model was developed to use a heart/lung sound signal as input, locate and separate the heart sound signal from the lung sound signal, modify the heart sound signal or lung sound signal by adding an abnormality such as a crackle or wheeze, respectively, and then providing output of a reconstructed modified signal. While developing the model, the aspect of supporting a real-time application was considered when researching and implementing algorithms. The intent is for the model to be used in an application involving the augmentation of medical equipment with pathological sounds to be used with virtual patients for training medical students.

1.6 Contributions

This dissertation provides an important contribution of investigating and proving the plausibility of applying an acoustic musical signal tempo and beat detection algorithm to heartbeat detection and localization. Specifically, the research focuses on

1. Applying the de facto standard tempo and beat detection algorithm developed by Eric Scheirer [5] to heart signal analysis in order to detect heart rate and location of heartbeats in a heart sound signal.
2. Utilizing the algorithm to characterize separated heart sound signals (input) and reference pathology signals in order to modify the reference signal to better match the input signal in terms of heartbeat rate and location of the heartbeats.
3. Utilizing the algorithm to verify the heartbeat rate of the adjusted signal.
4. Implementing Scheirer's algorithm in MatLab, with only minor changes, such as adjusting the ranges of the six frequency bands [5].
5. Investigating techniques for modifying and substituting real heart and lung pathology signals in real-time.

1.7 Dissertation Organization

This dissertation includes some background of concepts related to the research, provides a discussion of influential work, provides a detailed description of the research, and presents validation results and conclusions based on the research. The dissertation starts by providing some background on heart and lung sound characteristics and a discussion of published adaptive noise cancelation filters for reducing heart sounds from lung sounds in breath sound signals. The discussion of influential work focuses on the areas of augmentation of standard patients, heart and lung sound analysis, including techniques for localizing, reducing and separating heart sounds from lung sounds, and tempo and beat analysis of acoustic musical signals. The detailed research description includes descriptions of the model, including details about the input heart/lung signals, and the

techniques used for heart/lung sounds signal analysis and modification. The description provides details about the investigation of two techniques for heart sound/lung sound signal separation: Recursive Least Squares and Wavelet Transform, as well as a well known acoustic musical tempo and beat detection algorithm which used for heart rate detection and heartbeat localization. The description also elaborates on the substitution of heart and lung pathology signals, and the resulting recombined heart/lung sounds signal. Validation results are presented, which include both qualitative and quantitative results. And lastly, the dissertation concludes with a discussion of formulated conclusions based on the research as well as a discussion of possible applications.

CHAPTER 2

BACKGROUND

Since this dissertation is focused on analyzing and modifying heart and lung sound signals, some details about the characteristics of heart sounds and lung sounds are necessary. The frequency range for lung sounds is 25 – 1500 Hz and that of the heart sound is from 20 – 150 Hz. Characteristics of the heart sound signals are typically assessed in terms of both intensity and frequency. According to the pertinent literature review, though peak frequencies of heart sounds have been shown to be much lower than those of lung sounds, comparisons between lung sound recordings acquired over the anterior right upper lobe containing and excluding heart sounds show that power spectral density (PSD) in both cases is maximal below 150 Hz.

A review of research in the area of heart and lung sound analysis was performed to acquire an understanding of current capabilities in the localization and separation of heart sounds from lung sounds. The various techniques were reviewed with a focus on their efficiency and plausibility for use in a real-time application to a modified electronic stethoscope. Many papers on heart and lung sound analysis included in the literature review were selected to provide knowledge and insight about heart and lung sounds, as well as different filtering methods that are applied to these types of biological sound signals. While these efforts focused more on the lung sounds and removing the heart sounds, the methods are relevant for focusing on localizing heart sounds and removing/separating heart sounds from lung sounds. In particular, Gnitecki and

Moussavi [4] reviewed various work in the area of separating heart and lung sounds. Fifteen techniques for filtering heart sounds from lung sound recordings were reviewed. These techniques include linear adaptive filters, autoregressive modeling, moving average modeling, least mean square, fourth order statistics, recursive least squares, block fast transversal, and reduced order Kalman filters. Gnitecki and Moussavi [4] note that none of the reviewed studies examined the performance of heart-sound cancellation in the presence of spontaneous artifacts, and more importantly, that a common, standard method for separating HS from LS in chest-wall recordings has not been selected by the scientific community. They recommend that future studies on filtering heart sounds from lung sounds and on heart sound localization focus on challenging the performance of employed techniques by incorporating conditions in data recording that are relevant to clinical application in the areas of environment and respiratory and cardiac abnormalities [4]. In addition, it is clear that there is a need for an investigation of the performance of these different techniques when used for filtering heart sounds from lung sounds and heart sound localization in clinical applications of respiratory and cardiac abnormalities. Other methods of heart and lung sound analysis were also summarized as part of the literature review. These include additional work by Gnitecki, Moussavi, and Pasterkamp [6], [12], in reducing heart sounds from lung sounds, Chien, Huang, Lin, and Chong's [7] work, and the work presented by Yip and Zhang[8] , as well as the multiple papers included in the review [6]-[16]. There is a need for more research of the technique of reducing heart sounds from lung sounds by automated control and adaptive filtering. The previous work by Yip and Zhang [8] is limited in its possible application of extracting and interpreting breath sounds, due to the fact that the processing occurs on a separate pc

and not on the medical instrument. More investigating to speed up their algorithm may be needed to support the signal processing being performed real-time in the electronic stethoscope. In addition, the technique of using independent component analysis to separate heart and lung sounds should be further investigated to analyze its plausibility for use in an electronic stethoscope. Various functions should be investigated to provide an alternative to the FastICA function to ensure that heart and lung sounds are clearly discriminated [8]. FastICA is a popular algorithm, known for its efficiency for independent component analysis. FastICA is based on a fixed-point iteration scheme to maximize non-Gaussianity as a measure of statistical independence. Concern over the need for at least two input recording sources to separate heart sounds and lung sounds, precluded its use for signal separation in this study [8].

This thorough review of various techniques of filtering heart and lung sound signals helped narrow down the selection of the Recursive Least Squares and Wavelet Transform filtering techniques as possible candidates accurate and efficient separation and preservation of heart and lung sound signals.

The literature review resulted in identifying promising work by various researchers in the areas of augmenting medical equipment, heart and lung sound analysis, and tempo and beat estimation to support the hypothesis involving the M&S research for generating simulated outputs of medical diagnostics tools to supplement the training of medical students with human patient role players. A main focus was given to the limitations and needed enhancements of the work performed by McKenzie, *et al.* [1]–[3] in the area of simulating abnormal heart or lung sounds in an SP, as this is the foundation upon which the heart modification procedure is applied. A review of research in the area of heart and

lung sound analysis was performed to acquire an understanding of current capabilities in the localization and separation of heart sounds from lung sounds. The various techniques were reviewed with a focus on their efficiency and plausibility for use in a real-time application to a modified electronic stethoscope. Work on heart signal analysis was also reviewed to investigate techniques for identifying and analyzing normal and abnormal characteristics of the heart sound signal. Lastly, the algorithm for tempo extraction and beat detection by Eric Scheirer [5] was identified as a possible method for heart sound localization. Additional tempo and beat analysis research, more current than that of Eric Scheirer [5], was reviewed [17]-[36]. The goal of the investigation was to find an alternate beat detection algorithm, to that of Scheirer [5], for use in detecting heart rate and localizing heart sounds in heart sound signal.

2.1 Augmented Standardized Patients

As stated, a main focus of the research evaluation was on the work performed by McKenzie, *et al.* [1]-[3] in the area of simulating abnormal heart or lung sounds in an SP through the use of a modified electronic stethoscope and previously recorded heart sounds. This research is presented in the paper, “Augmented standardized patients now virtually a reality,” [1] and drew on the advanced the work of Hubal, Kizakevich, Merino, and West [36]. Hubal, *et al.* [36] utilized natural language processing and virtual patients to provide completely automatic yet unscripted training sessions, while providing a useful tool for outlining the steps for patient interaction and diagnosis.

While they were limited due to the human-computer interaction paradigm, McKenzie, *et al.* [1]–[3] attempted to provide a completely realistic experience by drastically enhancing this accepted medium of instruction.

It was noted that with a real or standardized patient, the learner was limited to hearing only the sounds of that single person, and that learning a variety of sounds would require examining many patients over time, often without direct supervision and feedback. Commercially available recordings of heart and lung sounds exist, but utilizing them would ignore the process of listening for the sounds, with the correct placement of the stethoscope, and would exclude simultaneous interactions with the patient. It was realized that augmenting SPs with the capability of portraying patients with an increased range of abnormalities would make the use of SPs an even more valuable teaching tool.

The work of McKenzie, *et al.* [1]–[3] was performed in multiple phases. The first phase of the research involved simulating abnormal heart and lung sounds in an SP. A student listened to an SP's heart and lungs through a modified stethoscope and heard pre-recorded sounds rather than the SP's. A functional prototype, consisting of a mannequin fitted with an electromagnetic generator and a movable sensor connected to the stethoscope head, was constructed. A tracking system was used to track the placement of the stethoscope, and when the tracking software detected that the sensor/stethoscope head was placed in an appropriate location, the software triggered the corresponding sound file to be played into headphones that the student was wearing. The researchers planned for the replacement of the mannequin with an augmented SP, which was incorporated into the follow on phases of research, as presented in “Medical student evaluation using augmented standardized patients: Preliminary results” [2] and “Medical student

evaluation using augmented standardized patients: New development and results” [3].

McKenzie, *et al.* [1] were successful in an initial validation of the augmented SP prototype, a mannequin, for listening to pre-recorded heart and lung sounds through a modified stethoscope. The sounds were heard when the head of the modified stethoscope was placed at any of four locations on a mannequin torso. The authors noted that there was nothing special in the use of the mannequin, and that a real human (SP) could have been augmented with their system [1]. These authors addressed this point in their follow on phase of research.

The second phase of the research involved augmenting the SP and performing a study using medical students evaluated in the annual Observed Structured Clinical Examination (OSCE), to formulate conclusions about the validity of using augmented SPs as a reliable medical assessment tool. With the augmented SP, the student would listen to an SP's heart and lungs through a modified stethoscope and hear pre-recorded sounds rather than the SP's. The main objective of the study was to determine the validity of using augmented SPs as a reliable assessment tool by presenting abnormal pathology. The study subjects were 105 fourth year medical students, and the study was completed in two halves over fourteen different days. The subjects listened for a carotid artery bruit (sound). It was noted that in patients with atherosclerosis, one might hear a characteristic sound (or bruit) caused by restricted or turbulent blood flow in one or more carotid arteries. In this study, subjects were asked if they detected an abnormal sound as they auscultated the neck areas of SPs. The students conducted physical exams on augmented SPs, including an auscultation of the left and right side of the SPs neck and reported whether or not they heard a carotid bruit. Of the 105 students, many were

excluded for the following criteria: the tracker did not indicate a stethoscope sensor in the hot zone, the bruit sound did not play, the student did not place the stethoscope in a correct anatomic position, or the student did not use the electronic stethoscope as their only instrument. Data from the remaining 53 students were organized as follows: 16 heard the sound when on, 19 did not hear when the sound was off, 1 heard when the sound was off, and 17 did not hear when the sound was on, a Chi-Squared test with 1 degree of freedom for the factors of sound on/sound off) vs. (heard/not heard) was used, and gave a value equivalent to 0.00101 chance that the sample distribution was attributed to randomness. The researchers had a high confidence that using the augmented SP system was a valid assessment tool, and planned for additional studies using more experienced trainees and clinicians as subjects to assess the realism of the augmented SP system and its validity for assessment.

McKenzie, *et al.* [2] were successful in using their augmented SP system to evaluate medical students in their standard OSCE testing environment. However, the results indicated that 1/3 of the students did not appropriately diagnose the abnormality. The authors noted that this might have been due to incorrect assumptions on their part. These assumptions included the thoughts that the students' hearing was normal so they should be able to detect a bruit; that students would note that a bruit was heard if in fact they heard one on their exam; and that the sound played into the earpiece at the correct time. For example, it is possible that students did not hear the bruit due to hearing loss from modern-day headphone usage. Another cause could have been limited exposure of the student to carotid bruits. It was noted that further analysis of non-augmented portions student examinations needed to be performed. The authors noted that the system was

limited in the sounds that it was capable of simulating [2]. The researchers planned to add additional abnormal sounds to their database. As with most technology, the desire to minimize the system components was present. An increase in realism would be gained by making the components smaller.

While the second phase of research involved simulating abnormal heart or lung sounds in an SP through the use of a modified electronic stethoscope and previously recorded heart sounds, the third phase of research activities included overlaying fine crackles along with real breaths of SPs. A student would hear this sound at the anterior lung bases after a maximal expiration or after the patient was recumbent for a prolonged period of time. The pre-recorded crackle and real breath sound were combined in real-time and played through the modified electronic stethoscope, to provide a realistic abnormal pathology to enhance the medical student hands on training. The focus of the research was in synchronizing the virtual crackle sound with the SP's real breath sound. The authors noted that fine crackles are heard mostly at the end of inspiration, and in specific locations upon chest auscultation [3]. Instead of using a tracking system, as in the previous phase, this phase used a simple method of identifying both the correct point of inspiration to combine the virtual crackles and the location on the body at which the sounds should be combined. This method used a SP with a wireless remote controller to allow the SP to signal the correct timing of respiration. The SP clicked the controller towards the end of his/her inspiration, and then when the computer detected the signal, the virtual crackle sound was played to computer audio, and the student would hear the combined virtual sound and real breath sound through the modified electronic-stethoscope, which was connected to the computer using a wireless transducer and

receiver. This method allowed for the real breath sound directly from the SP to be combined with a pre-recorded crackle sound at the SP's end of inspiration upon chest auscultation in real-time.

The third phase of research furthered the concept of augmented SPs. The system was not fully automated, as the SP still had to signal the end of his/her inspiration. The authors concluded that it would be more beneficial for medical student training if the system was capable of providing fine crackle and additional abnormalities, without requiring SP manually controlling when sounds are heard, but instead triggering sound presence based on the natural biological functions of the SP. The research described in this dissertation has focused on this need.

There is great promise in furthering the work of McKenzie, *et al.* [1]–[3] in the area of augmented SPs. The previous work of McKenzie, *et al.* [1]–[3] has been very successful in using a modified stethoscope combined with augmented SPs that have the capability of portraying patients with an increased range of heart and lung abnormalities, and will make the use of SPs an even more valuable teaching tool for medical students. The third phase of research of McKenzie, *et al.* [3] was successful in combining simulated crackles into real SP breath sounds. This proof of concept system evaluation was performed by an EVMS doctor experienced in SPs and training auscultation, and provided evidence that the system could be a useful and integral part of auscultation education with expanded fields of interest with abnormalities. The next logical step in the research was to make the system more automated by removing the “human in the loop” control of the simulation. In the third phase of research, the augmented SP system was not fully automated, as the SP still had to signal the end of his/her inspiration.

It was recognized that it would be more beneficial for medical student training if the system was capable of providing fine crackle and additional abnormalities without requiring SP manually controlling when sounds are heard, but instead triggering sound presence based on the natural biological functions of the SP. This is the identified need that prompted the research described by this dissertation.

2.2 Heart and Lung Sound Analysis

This dissertation research involves the real-time modifying of the lung and heart sound signal, specifically the heart signal. To accomplish this, the heart sound signal is separated from the lung sound signal. In this case, the heart sound signal is the signal of interest, not the lung sound, as presented in most of the reviewed papers on heart and lung sound analysis. The papers on heart and lung sound analysis included in the literature review were selected to provide knowledge and insight about heart and lung sounds, as well as different filtering methods that are applied to these types of biological sound signals. While these efforts focused more on the lung sounds and removing the heart sounds, the methods are relevant for focusing on localizing heart sounds and removing/separating heart sounds from lung sounds. In particular, Gnitecki and Moussavi [4] reviewed various work in the area of separating heart and lung sounds. Fifteen techniques for filtering heart sounds from lung sound recordings were reviewed. These techniques include linear adaptive filters, autoregressive modeling, moving average modeling, least mean square, fourth order statistics, recursive least squares, block fast transversal, and reduced order Kalman filters. Gnitecki and Moussavi [4] note that none of the reviewed studies examined the performance of heart-sound cancellation in the

presence of spontaneous artifacts, and more importantly, that a common, standard method for separating HS from LS in chest-wall recordings has not been selected by the scientific community.

In the study presented in their paper, “Recursive least squares adaptive noise cancellation filtering for heart sound reduction in lung sound recordings,” Gnitecki, Moussavi, and Paterkamp [6] discuss their research in applying recursive least squares (RLS) adaptive noise cancellation (ANC) filtering for heart sounds reduction. Based on both quantitative and qualitative results, the authors indicate that the RLS-ANC may be used to adequately and accurately localize and remove HS in a single, automated method for filtering HS from LS. They did discuss the large processing time of the RLS-ANC, but feel this is insignificant to achieve LS preservation. The RLS-ANC method is capable of HS localization, but requires a separate procedure to localize HS and apply the locations to the reference. Though there was a concern of the efficiency of the algorithm due to the need dynamically create the reference signal, this method was selected as candidate heart and lung sound separation technique, due to the results presented by ,” Gnitecki, Moussavi, and Paterkamp [6].

Other methods of heart and lung sound analysis were also summarized as part of the literature review. In their paper, “Reduction of heart sounds from lung sounds by adaptive filtering,” Iyer, Ramamoorthy, Fan and Ploysongsang [9], note that due to its simplicity and non-invasiveness, auscultation of the chest is a widely used diagnostic method of physicians. They note the interest in lung sound analysis using time and frequency domain techniques to increase its usefulness in diagnosis, and the common problem of lung sounds being contaminated by incessant heart sounds, which interfere in

the diagnosis based on, and analysis of, lung sounds [9]. To minimize the effect of heart sounds, the authors present an alternative to using linear high pass filters, which, also eliminates the overlapping spectrum of breath sounds. They show how adaptive filtering can be used to reduce heart sounds without significantly affecting breath sounds. The technique is found to reduce the heart sounds by 50-80 percent. This work influenced the decision to utilize adaptive filters for separation of heart sounds and lung sounds as part of the research described in this dissertation.

In their paper, "Adaptive reduction of heart sounds from lung sounds using fourth-order statistics," Hadjileontiadis and Panas [10] present an adaptive heart-noise reduction method, based on fourth order statistics (FOS) of the recorded signal. Without requiring a recorded "noise-only" reference signal, this algorithm uses adaptive filtering to preserve the entire spectrum, and the filter is independent of Gaussian uncorrelated noise and insensitive to the step size parameter. The authors note that the algorithm converges fast with small excess errors, and requires a very small number of taps, due to the narrowband nature of HS [10]. Results from experiments with healthy subjects indicate a local HS reduction equal to or greater than 90%.

In their paper, "A Wavelet-based reduction of heart sound noise from lung sounds," Hadjileontiadis and Panas [11] present another method of reducing heart sounds from lung sounds. The method utilizes a wavelet transform domain filtering technique as an adaptive de-noising tool for lung sounds analysis. The wavelet transform produces multiresolution representations of the signal, which are used for signal structure extraction. In addition, a separation of the non-stationary part of the input signal (heart sounds) from the stationary part (lung sounds) occurs from the use of hard thresholding in

the wavelet transform domain. As a result, the location of the heart sound noise (first and second heart sound peaks) is automatically detected, without requiring any noise reference signal. The authors present experimental results, which show that the application of this wavelet-based filter on lung sound signals, which include heart sounds, results in an efficient reduction of the heart sound, producing an almost noise-free output signal. The authors feel that, due to its simplicity and its fast implementation, the presented method can easily be used in clinical medicine.

Gnitecki, Hossain, Pasterkamp, and Moussavi presented their continued research of adaptive filtering techniques in the paper, “Qualitative and quantitative evaluation of heart sound reduction from lung sound recordings” [12]. Gnitecki, Hossain, Pasterkamp, and Moussavi [12]-[14] have completed considerable research in studying lung sounds (LS) to monitor lung airway status. They realized that the presence of heart sounds combined with complicates the signal processing needed to evaluate flow-specific lungs sounds as a function of airway conditions for diagnostic purposes. With the need to filter heart sounds from lung sounds and the fact that there is not an established filtering method, the researchers performed an assessment of utilizing the RLC linear adaptive filter and the wavelet and the wavelet transform (WT) – based de-noising, in an effort to identify an acceptable method for separating heart sounds from lung sounds in chest-wall recordings [12].

Based on both the quantitative and qualitative results, the authors indicate that the RLS-ANC filter was superior to the WN-ANC filter for the specific tested signals [12]. The processing time of the RLS-ANC filter was ten times that of the WT-ANC filter, but the authors feel this is insignificant to achieve lung sound preservation. Both methods

were capable of heart sound localization, with RLS-ANC requiring a separate procedure to localize heart sound and apply the locations to the reference. With its superior performance, the authors propose that RLS-ANC may be used to adequately and accurately localize and remove heart sound in a single, automated method for filtering heart sound and lung sound.

The work by Hadjileontiadis and Panas [10], [11], [15] heavily influenced the presented research. Both the FOS and WT methods are useful for filter signals. However, due to the published results of the extended research by Hadjileontiadis and Panas [11], [15], and Gnitecki , Hossain, Pasterkamp, and Moussavi [12], the WT was selected as a candidate along with RLS for separating heart and lung sounds in the presented research. The work by Gnitecki , Hossain, Pasterkamp, and Moussavi [4], [6], [12], and Hadjileontiadis and Panas [10], [11], [15] on applying adaptive filtering to separating heart and lung sound signals helped focus the dissertation study. The published results of the work of both sets of researchers showed the RLS and WT filtering methods are viable solutions for separating heart and lungs in an effective and efficient manner relevant for the application address by this study.

2.3 Heart Sound Analysis Using Tempo, Onset, and Beat Analysis of Acoustic Musical Signals

In order to modify the heart sounds in a real-time manner, research is needed to select powerful, yet computationally efficient algorithms for analyzing and modifying heart sound signals. Published work in this area has highlighted a need for further research to identify efficient techniques for heart signal analyzes. As noted by Ellis et al. [17], the

derivation, from beat tracking, of a sequence of beat instants, involves satisfying two constraints. First, the selected instants should generally correspond to moments in the audio where a beat is indicated, for instance by the onset of a note played by one of the instruments. Secondly, the set of beats should reflect a locally constant inter-beat-interval, since it is this regular spacing between beat times that defines musical rhythm. These dual constraints also match the characteristics of the human heartbeat contained in the heart and lung sounds signal.

The need for further research to explore applying a tempo and beat analysis algorithm to the heart sounds signal to perform heart sound analysis, including detecting the heart rate and location of the heartbeats, was identified. The summaries of previous research in beat and tempo estimation provide possible techniques that may successfully be applied to heart and lung sound analysis. While the reviewed algorithms use some similar techniques, they each incorporate different assumptions of the input signal as well as variations in the techniques.

In the paper, “Tempo and beat analysis of acoustic musical signals,” [5] Scheirer presents a method for using a small number of band-pass filters and banks of parallel comb filters to analyze the tempo of, and extract the beat from, musical signals. It was noted that the analysis is performed causally, and can be used to estimate when beats will occur in the future. The author provides a brief summary with noted limitations of past (prior to 1998) work in the area of tempo and beat analysis, and points out that this work is characterized as a transcriptive metaphor for analysis, i.e. the music is first segmented into notes, onsets, timbres, etc. Post processing algorithms are then used to group rhythms and track beats.

In this paper [5], Scheirer presents psychoacoustic demonstrations, which lead to processing simplifications for beat tracking, a detailed description of the utilized algorithms, a description of the validation process, and a discussion of future work. Two important realizations that the author discusses are 1) that “notes” are not required for hearing rhythm. It is possible to develop algorithms for pulse extraction to rhythmically analyze a musical signal (for human listeners), which operate on the preserved amplitude envelopes of the filter banks output and not on “notes”. 2) Separating the signal into subbands and maintaining the subband envelopes separately is necessary to do accurate rhythmic processing. A description of the algorithm is as follows: A filter bank is used to divide the input signal into six subbands. The amplitude envelope and derivative are calculated for each of the subbands. These derivatives are passed on to another filter bank of tuned resonators. The resonator, whose frequency matches the rate of periodic modulation of the envelope derivative, will phase-lock. The outputs of the resonators are examined to identify the phase-locked resonator. This information is tabulated for each of the band pass channels, summed across the frequency filter bank to arrive at the frequency (tempo) estimate for the signal, and then referenced back to the peak phase points in the phase-locked resonators to determine the phase of the signal. The algorithm was tested for audio sampling rates from 8 kHz to 44.1 kHz, and gave equivalent qualitative performance for all of the tested rates in this range. Scheirer [5] goes on to show that the beat-tracking procedure can be run in real-time on an advanced desktop workstation.

Scheirer [5] describes an algorithm, which can successfully beat-track digital audio signals representing many different musical types. The music does not have to contain

drums or other specific timbres, and does not have to conform to any predetermined set of musical templates. Scheirer [5] identifies various areas where further development or improvement could occur. These include the frequency filter bank, envelope sampling rate, analysis of frame rate, and behavior tuning. He recommends that further testing with different frequency filter banks other than a six-channel sixth-order IIR. It is important to investigate various types of filters to reduce computational cost, as there is CPU load for implementing high-order filters in real-time on high bandwidth audio. The author notes various areas that need to be investigated to control the tradeoff between program speed and accuracy. One area addresses the fact that the decimation rate of the channel envelopes affects the speed and performance of the system. A slow envelope-sampling rate is important because there are many resonator frequencies that cannot be accurately represented with integer delays in comb filters, and the phase extraction can only be performed with accuracy equal to the envelope-sampling rate. If a fast envelope sampling rate is used then the comb filters will have more computations, since the number of multiplies in the filter varies proportionately to this sampling rate. While the author recommends an envelope-sampling rate of 100 Hz, more analysis of envelope sampling rates should be investigated. The author notes that the frequency of examining and summing outputs and internal states of the resonators strongly affects the performance of the program. Therefore analysis of optimum frame rate should be performed. The behavior of the algorithm can be tuned with the α parameters in the comb filters. These values control whether to value old information or new information more highly. The author notes that manipulating these parameters is computationally similar to manipulating the windowing function of a narrowed autocorrelation. The work

of Eric Scheirer [5] has become the de facto reference for most in the area of tempo and beat analysis. The accuracy and efficiency of the algorithm indicated its relevance to heart and lung sound analysis. It was noted that further research of utilizing Scheirer's algorithm [5] for heart sound analysis should be performed. This includes utilizing different frequency filter banks, investigating various types of filters to reduce computational cost, as there is CPU load for implementing high-order filters in real-time on high bandwidth audio. In addition, the author had noted various areas that need to be investigated to control the tradeoff between program speed and accuracy; these areas include envelope sampling rate, analysis of frame rate, and behavior tuning.

LaRoche [18] based his research on the previous work of Scheirer [5], but incorporated the assumption of constant tempo. Generally, this assumption may be acceptable for heartbeat sound analysis. But, it may preclude performing heartbeat sound analysis and signal modification on inputs of irregular heartbeats. This needs to be further investigated. LaRoche [18] noted that his algorithm does not perform well on tracks that do not contain sharp attacks or transients. Research is needed to see if heartbeats have sufficiently sharp transients. LaRoche [18] notes that the algorithm is computationally expensive and offers multiple areas to improve the algorithm's efficiency. This is a very important research area for applying the algorithm in an embedded, real-time system.

Alonso, David, and Richard's work [19], [20] improves LaRoche's work [18] by using an optimal filter to approximate the derivative and obtain a high performance onset detector, which is integrated into a tempo tracking algorithm. Further research is needed to see if the algorithm would provide valid results when applied to heart sound signals to

address the previously discussed limitations of the algorithm [19], [20]. In addition, further research should address the previously mentioned issues for a real-time implementation. It may be difficult to overcome the need for future signal samples for block-wise processing. The non-causality of the thresholding filter used in the detection function would have to be addressed, as well. This algorithm also assumes a constant tempo and would need similar analysis to that of LaRoche's algorithm [18].

Because Scheirer's algorithm [5] was ground breaking, it was felt that none of the published research that built on his work is better suited to support real-time heart sound signal analysis; therefore, Scheirer's algorithm [5] was selected for this dissertation.

2.4 Development Environment

The development environment included the MatLab software programming language, and use of both the Signal Processing Toolbox and Wavelet Transform (WT) Library as a basis to implement the heart and lung sound separation, modification and heartbeat detection and localization algorithms. The MatLab Signal Processing Toolbox™ provides standard algorithms for digital signal processing. The toolbox and WT library were used to visualize the heart and lung sound signals in both the time and frequency domains; to compute FFTs for frequency domain computations including convolution; to implement FIR low pass, high pass and band pass filters; to implement modulation, resampling, and other signal processing techniques.

The Welch Allyn Meditron™ electronic stethoscope system was used to acquire sound files from live patients. The stethoscope system was configured for various frequency settings to attempt to isolate heart and lung sounds, which occur at specific

frequencies. While this attempt was made to isolate heart and lung sounds, the recording process still picks up other body sounds, which were included in the input files and may affect the results of the separation, modification and heartbeat detection and localization portions of the model.

The sound recordings were provided in the Waveform Audio File format, WAV. The WAV files are digital representations of the recorded biological sound signals. It is recognized that the processing including reading and writing, of these sound files can affect the accuracy of the sound signals. When possible, the use of the files was minimized and the signal data manipulated at various portions of the model was stored in memory rather than being read and written to files.

CHAPTER 3

RESEARCH DESCRIPTION

The dissertation study was performed, in order to further the work of McKenzie, *et al.* [1]-[3] in the area of augmented SPs. The study focused on the identification of techniques that are conducive to supporting real-time pathology signal analysis and modification. The research focused on two areas: 1) the plausibility of applying the acoustic music signal tempo and beat detection algorithms of Scheirer [5], 2) determining an optimum technique of separating heart sounds from lung sounds from the two of the techniques reviewed by Gnitecki , Pasterkamp, and Moussavi [12]: including the RLS-ANC and the WTC-ANC algorithm developed by Hadjileontiadis and Panas [11].

3.1 Model Description

To further the work of McKenzie, *et al.* [1]-[3] in the area of augmented SPs, a study was conducted to develop a model to use a heart/lung sound signal as input, locate and separate the heart sound signal from the lung sound signal, modify a reference pathology heart signal to resemble the original separated heart sound signal in terms of heart rate and heartbeat locations, combine the modified pathology heart sound signal with the original lung sound signal, and then provide output of a reconstructed modified signal in an acceptable real-time time-frame. It is intended that the model will be used in an application involving the augmentation of medical equipment with pathological sounds to be used with virtual patients for training medical students. A description of the model is presented in Fig. 1. The functionality of each stage of the model is described in the following sections. The model was developed using the previously described

development environment, including the MatLab software programming language, including use of both the Signal Processing Toolbox and Wavelet Transform Library.

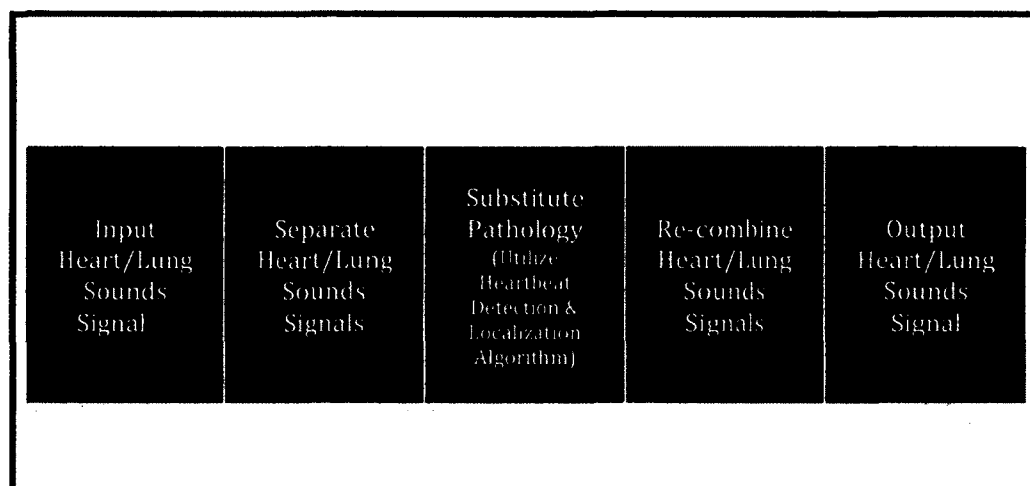


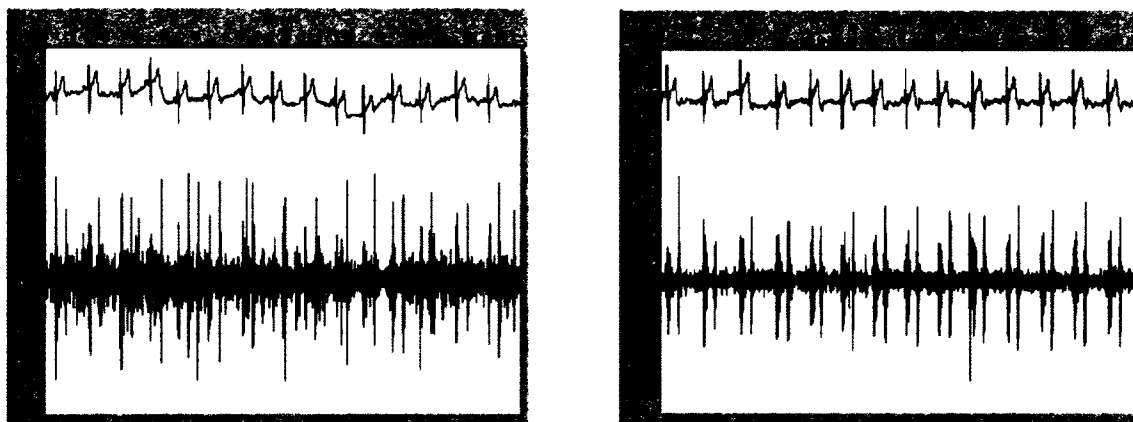
Fig. 1. Overview of model for virtual pathology using signal analysis and modification.

3.2 Heart/Lung Signals (Input and Reference Data)

Various audio files of normal and abnormal hearts sounds, as well as lung sounds, and combined heart/lung sound were acquired, from the Medical Imaging Diagnosis and Analysis Laboratory of Old Dominion University, for use in the dissertation study. The input files, are in the WAV format. The signals in the files are sampled at 44.1 KHz and included signals from normal breathing, deep breathing, breath holding as well as signals from the aortic, pulmonary, mitral, and tricuspid auscultation sites. In addition, various files containing heart and lung pathology, such as a heart murmur, a lung asthma wheeze, and lung crackles were also utilized. A list of files, with descriptions, is included in Appendix A: Description of Input and Reference Heart/Lung Signals.

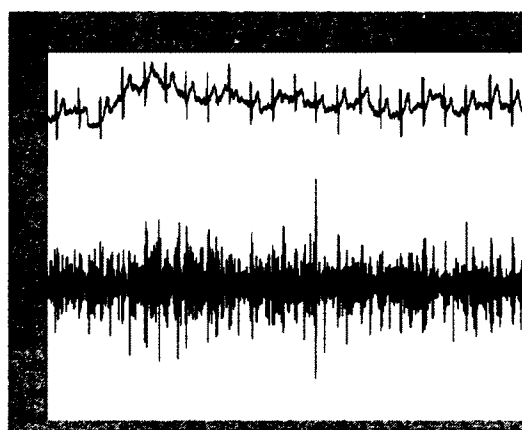
The ECG and sound signals, used in the research, were collected from the pulmonary region. The Welch Allyn Meditron™ electronic stethoscope was used to gather the data. For better signal acquisition by reducing noise, all of the signals were collected using conductive gel. The built-in filter of the stethoscope was set to low frequency, medium frequency, or high frequency levels. Each signal was collected for 15.5-seconds. Examples of signals collected in the pulmonary region, with a medium frequency setting, are shown in Fig. 2.

Fig.2. contains three sets of plots corresponding to the acquired signal when a patient was exhibiting a) normal breathing, b) holding breath, and c) deep breathing. Each of the three sets contains two (approximately) 15.5-second duration plots. The upper plots show the ECG signal and the lower plots show the heart/lung sound signals. Each plot has a time domain in seconds and a voltage range in millivolts. It can be seen from each of the ECG plots and clearly in the holding breath plot (which lacks lung sounds) that there are approximately 15 heartbeats in a 15.5-second sample time period, which indicates the patient's heart rate at approximately 60 bpm.



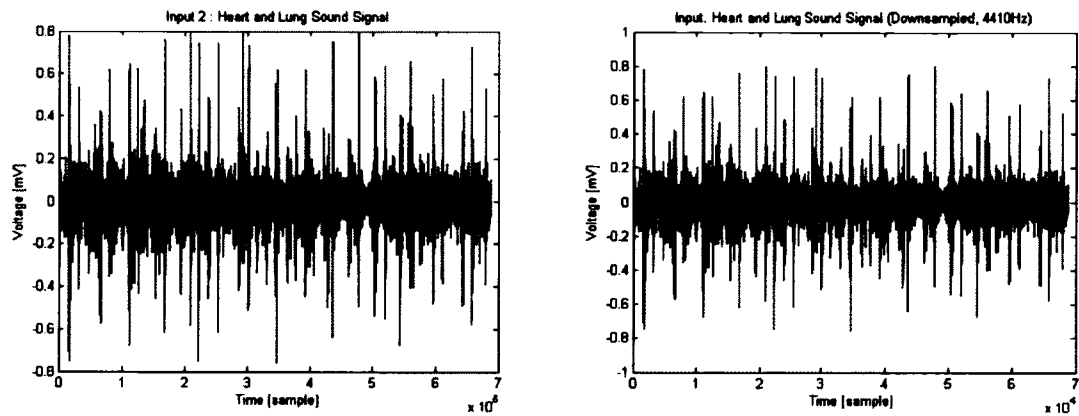
(a) Normal breathing

(b) Holding breath



(c) Deep breathing

Fig. 2. Pulmonic area reference signals.



(a) Original Heart/Lung Sound Signal

(b) Downsampled Heart/Lung Sound Signal

Fig. 3. Original and down sampled input signal.

The input signals were preprocessed prior to being filtered for heart and lung sound separation. The preprocessing included lowpass filtering, downsampling by a factor of 10, and normalization. The original input signal was sampled at a frequency of 44.1 KHz and, after downsampling, the new sampling frequency was 4.41 KHz. To preclude aliasing of frequency components higher than the Nyquist rate of 2.2 KHz, an order 30 FIR filter with cutoff frequency of 1764 Hz $[0.8 \cdot (44100/2)/10]$ was applied prior to downsampling. The cutoff frequency was well above any heart or lung sound frequency components. Examples of a original input signal and down sampled signal are shown in Fig. 3. The 15.5-second original has a time domain measured in time samples at a sampling rate of 44100 Hz and a signal value range in millivolts. The 15.5-second filtered and downsampled (factor of 10) signal in Fig. 3b. shows time domain samples with a sampling rate of 4410 Hz and a signal value range in millivolts. It can be seen, when comparing both plots, that the filtering and downsampling reduced the data set for efficient processing without affecting the integrity of the signal.

3.3 Heart/Lung Sounds Signal Analysis: Heart Sound/Lung Sound Separation

While it was envisioned that the heart sounds and lung sounds would be required to be separated prior to applying the heartbeat detection and localization algorithm to characterize the heart signal, an investigation into the feasibility of applying the algorithm to the input signal without heart and lung sound separation was conducted. The heartbeat detection and localization algorithm was applied to a subset of input files used for the study, as previously described. The set included signals acquired for two different patients exhibiting “normal breathing” from the aortic, pulmonic, tricuspid and mitral auscultation sites. From visual inspection of the ECG signal plots, one patient exhibited a heart rate of approximately 60 bpm and the second patient exhibited a heart rate of approximately 80 bpm. For each file, an estimate of the location of the first heart beat was acquired from visual inspection of the time domain representation of the input heart and lung sound signal. The beat detection algorithm was applied to a total of 8 sound signal data sets. The results are shown in TABLE I. For sound signal files corresponding to the patient with a beat rate of approximately 80 bpm, the beat detection algorithm calculated rates ranging from 46 to 124 bpm. For sound signal files corresponding to the patient with a beat rate of approximately 60 bpm, the beat detection algorithm calculated rates of 95 and 117. In addition, the WTC-ANC filter was applied to each of the input files to separate the heart sounds from the lung sounds. The beat detection algorithm was then applied to each of the separated heart sound signals. The calculated heart rates and first heartbeat locations are comparable to the estimates. The results are also included in TABLE I. Both the variance in calculated heart rates and first beat locations from the input heart and lung sound signals and the consistent and accurate calculations for the

separated heart sound signals shows that the beat detection does not accurately detect heart rate on signals containing both heart and lung sounds and that sounds must be separated prior to utilizing the algorithm to detect heart rate.

TABLE I
BEAT DETECTION OF INPUT HSLs SIGNAL

Signal	InputHSLs HR (bpm)	Input HSLs 1st Location (sample #)	Visual HR (bpm) ^a	Visual 1 st Location (sample #) ^b	Separated HS HR (bpm)	Separated HS 1st Location (sample #)
Pulmonic mid Normal Breathing	82.95	1262	~ 80	~ 2200	81.67	2179
Mitral Normal Breathing	124.42	44	~ 80	~ 1200	84	1219
Middle Normal	116.89	1282	~ 60	~ 1200	56.26	1323

^a Visual estimation from ECG signal plot. ^b Visual estimation from sound signal plot.

In order to perform heart signal analysis, the heart sound signal was separated from the lung sound signal. Unlike what was presented in most of the reviewed papers on heart and lung sound analysis, the heart sound signal was the signal of interest, not the lung sound signal. Research was performed to select an optimum technique for separating the heart sound signal from the lung sound signal of an SP in an efficient manner, while preserving both signals.

3.3.1 Heart and Lung Sounds Separation Techniques

Various methods of heart and lung sound analysis have been summarized in Section 2.2

Heart and Lung Sound Analysis. These include Gnitecki's and Moussavi's review [4] of research in the area of separating heart and lung sounds. While these efforts focused more on the lung sounds and removing the heart sounds, the methods are relevant for focusing on heart sounds and removing/separating lung sounds. Gnitecki and Moussavi [4] summarized fifteen techniques for filtering heart sounds from lung sound recordings, including linear adaptive filters, autoregressive modeling, moving average modeling, least mean square, fourth order statistics, recursive least squares, block fast transversal, and reduced order Kalman filters.

Utilizing an efficient algorithm is critical to separating the heart sounds from the real-time pathology of the patient in training medical students in auscultation. Upon further review of the research identified in the literature review, two methods were identified to fulfill this requirement, and were implemented. The first method is the Recursive Least Squares adaptive noise cancellation (RLS-ANC) method developed by Gnitecki, Pasterkamp, and Moussavi [6]. The RLS adaptive filtering scheme consists of a transversal filter with finite-duration impulse response (FIR) and an RLS adaptation algorithm, which updates the tap weights of the transversal filter so that the mean square error (MSE) is minimized and an estimate of the desired output, lung sound signal results, with the heart sound signal being provided in the filter output error.

The second implementation is a wavelet transform adaptive noise cancellation (WT-ANC) filter, based on the work by Hadjileontiadis and Panas [11]. This filtering technique was also used for the localization of the heart sounds. The authors have shown that the application of this wavelet-based filter on lung sound signals, which include heart sounds, produces an almost noise-free, i.e. heart sound-free, output signal. It was

anticipated that this would be a viable solution based on the simplicity of the algorithm and its fast implementation, as well as based on both the qualitative and quantitative results presented by Gnitecki, Hossain, Pasterkamp, and Moussavi [12]. As shown in the work of Gnitecki, Hossain, Pasterkamp, and Moussavi [12], [based on both a quantitative and qualitative assessment, both techniques are capable of heart and lung sound signal separation and heart sound localization. Gnitecki, Hossain, Pasterkamp, and Moussavi [12] identified advantages and disadvantages to applying each technique. For instance, the processing time of the RLS-ANC filter was ten times that of the WT-ANC filter. This was a concern due to the objective of efficiency. It was anticipated that WT-ANC filter processing time would be adequate. While, both methods are capable of HS heart sound localization, the RLS-ANC requires a separate procedure to localize heart sounds and apply the locations to the reference.

The research investigated using the RLS-ANC filter developed by Gnitecki, Pasterkamp, and Moussavi [6] and the WT-ANC filter developed by Hadjileontiadis and Panas [11], as well as a combination of both filters for the separation of the heart sound signal from the lung sound signal, to enable the heart sound signal to provide localization of heart sounds (first and second heart sound peaks), which were then used in the heart signal analysis and modification.

For this study, acceptable separation is defined as separated signals having minimal lung sound components in the heart sound signal and visually unnoticeable or at least minimal heart sound components in the lungs sound signal. The PSD of the separated signals should correlate with the time domain representations, with the power of the heart sound signal being maximal below 100 -150 Hz and decreasing for frequencies after 150

Hz. The greater the slope of the graph after 150 Hz, the less lung sounds are present in the signal. There will always be some lung sounds present. The PSD of the lung sound signal should be similar, with the threshold being between 150 – 200 Hz. The PSD should be lower between 0 – 40 Hz, where only heart sounds are present.

Both methods were able to separate the heart sounds from the lung sounds. The RLS_ANC method did take considerably longer to execute. The separated heart sound signal from the WT-ANC was more conducive accurate heart rate and heartbeat location calculations by the heartbeat detection and localization.

The feasibility of using separated HS output of the WT-ANC filter as input to RLS_ANC filter was also investigated. Three attempts were made. The first attempt used an unfiltered pulmonic holding breathing sound file as a reference for applying the RLS-ANC filter to the pulmonic normal breathing file. Since a holding breath signal typically contains minimal lung sounds, it was hopeful that this could be used as a reference of the heart sound signal. However, the results of the RLS-ANC signal separation were not favorable. Heart sound components correlating to heartbeats in the input signal were visually noticeable in the separated lung sound signal. The separated heart signal contained location and amplitude accurate heart sound components in the first 5% of the signal and then the amplitude was drastically reduced. The PSD of the resultant heart sound signal showed maximum power well below 100 Hz, which is typical of a heart sounds, but the power was drastically reduced from -30 dB/Hz to -70 dB/Hz, most likely due missing heart sound components which were included in the separated lung signal. The PSD of the lung sound signal mirrored the input signal with maximum power of -30 dB/Hz for the frequency range from 0 – 150 Hz, which is expected of a

signal containing both heart and lung sounds. It was decided that this method would not be used for heart and lung sound separation.

The second attempt used the WT-ANC separated heart sound signal from the pulmonic holding breathing sound file as a reference for applying the RLS-ANC filter to the pulmonic normal breathing file. Again, since a holding breath signal typically contains minimal lung sounds, it was hopeful that this could be used as a reference of the heart sound signal. However, the results of the RLS-ANC signal separation were not favorable. The heart and lung sound signals were not adequately separated. The resulting heart sound signal was very sparse and contained minimal heart sound components, and the components were drastically reduced in amplitude. Both heart and lung sound components were present in the lung sound separated signals. The PSD of the heart sound signal showed a very low power due to the fact that many of the heart sound components were included in the lung sound signal. The PSD of the resultant heart sound signal showed maximum power well below 100 Hz, which is typical of a heart sounds, but the power was drastically reduced from -30 dB/Hz to -70 dB/Hz, most likely due missing heart sound components which were included in the separated lung signal. The PSD of the separated lung sound signal also corresponded to having both sound components present. The PSD of the lung sound signal mirrored the input signal with maximum power of -30 dB/HZ for the frequency range from 0 - 150 Hz, which is expected of a signal containing both heart and lung sounds. The separated heart sound signal did possess high correlation in heart sound locations with the original input signal. Since the separated heart sound signal did contained sparse heart sound components, it

was not conducive to supporting accurate heart rate and heartbeat location calculations by the heartbeat detection and localization algorithm.

The third attempt used the WT-ANC separated heart sound signal from the pulmonic normal breathing sound file as a reference for applying the RLS-ANC filter to the pulmonic normal breathing file. The results were better than using the holding breath as a reference, but were still not sufficient. The heart and lung sound signals were not adequately separated. The separated heart sound signal contained more heart sound components, however, both heart and lung sound components were present in the separated lung sound signal. The PSD of the original sound signal contained maximum power of -30 dB/Hz for the frequency range from 0 - 150 Hz, which is expected of a signal containing both heart and lung sounds. The PSD of the separated heart signal did not contain lung sound components as the signal showed maximum power well below - 100 Hz, which is typical of a heart sounds, but the power was drastically reduced from - 30 dB/Hz to -70 dB/Hz, most likely due missing heart sound components which were included in the separated lung signal. However, if lung sounds were present, the power would have been maximum from 0 –150 Hz. The PSD of the separated lung sound signal also corresponded to having both sound components present. The power was maximum at -30 dB/Hz from 0 to 150 Hz, similar to the input signal.

The WTC-ANC filtering method was selected to separate the heart sound and lung sound signals for two reasons. The predominant reason is that the WT filtered HS signals provide an efficient and accurate separation of the HS and LS. The algorithm performs ten times faster than the RLS filtering method, with out requiring a reference signal to be generated or acquired. The filtered heart sound signal provides an accurate

representation of the heart sounds to be used as input to the heartbeat detection and localization algorithm.

3.3.2 Description of Wavelet Transform Filtering Technique

The WT-ANC filter as developed by Hadjileontiadis and Panas [11]. The WTC-ANC is a wavelet transform based filter that separates stationary and non-stationary signals. The filtering scheme combines the efficiency of multi-resolution analysis with hard thresholding and has been proven successful in heart sound noise reduction of lung sounds. Published work by Gnitecki, Hossain, Pasterkamp, and Moussavi [12] has shown that the WT-ANC filter provides high de-noised signal quality without requiring any reference signal, with low computational cost and fast and easy implementation.

The proposed algorithm is a wavelet domain filtering technique, based on the fact that explosive peaks in time domain have large signal over many wavelet scales, while 'noisy' background dies out swiftly with increasing scale. When applying the filter to a signal containing heart and lungs sounds, the peaks represent heart sounds and the 'noisy' background represents the lung sounds. An N sample signal is considered noisy or incoherent relative to a basis of waveforms if it does not correlate well with the waveforms of the basis [11]. From this idea, the separation of heart sounds from lung sounds becomes a matter of extracting the breath sounds. The heart sounds, contained in the non-stationary part of the input signal are separated from the lung sounds, which are contained in the stationary portion of the signal. The filtering scheme is shown in Fig. 7.

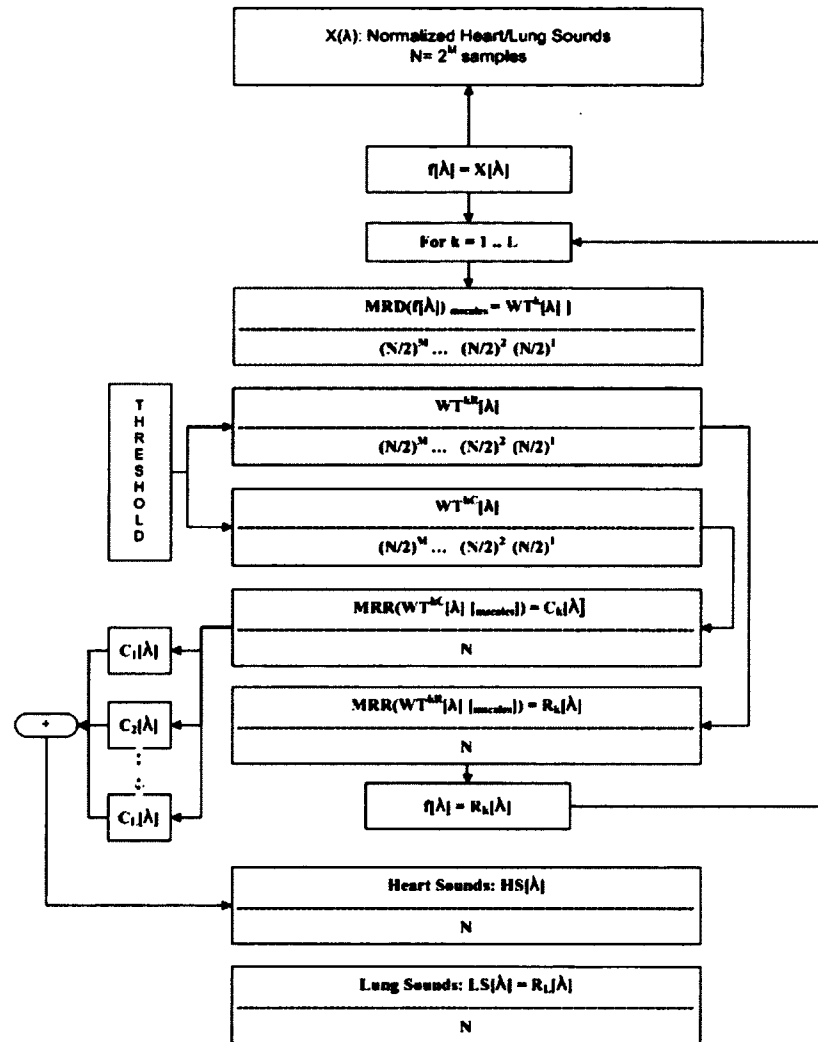


Fig. 4. WTC-ANC filter scheme.

The scheme utilizes Daubechies Quadrature Mirrored filters of different length (2dB to 12 dB), and includes an iterative multi-resolution decomposition - multi-resolution reconstruction (MRD – MRR) process to form different levels of noise separation. The input to the algorithm is length 2048 sample windows of the normalized heart and lung sound signal. Specifically, at k iteration, the WT of $f(u)$, (for $k = 1$, $f(u) = X(u)$, $u = 1, \dots, N$, where $X(u)$ is the normalized input signal) at m adjacent resolution scales ($m = 1, \dots, M$, where $M = \log_2 N$) is first calculated, using previously-defined

libraries of orthonormal bases. The resulted WT coefficients at j scale are compared with a hard threshold, defined as follows: $\text{THR}_j^k = \alpha_j^k \cdot F_{adj}$, where α_j^k is the standard deviation of WT at k iteration and j scale and F_{adj} is an adjusting multiplicative factor, used to sustain the threshold at high value, at different scales. A factor of 3.0 was used [18], though the factor can vary from 2.5, 2.6, and 2.7 according to Gnitecki, *et al.* [15]. From this comparison, the WT coefficients are divided into big ($>\text{THR}_j^k$) and small ($<\text{THR}_j^k$) ones, $\text{WT}^{\text{kC}}(\lambda)$ and $\text{WT}^{\text{kR}}(\lambda)$, respectively. If the signal $f(\lambda)$ is coherent, then applying MRR (m scales) to $\text{WT}^{\text{kC}}(\lambda)$ and $\text{WT}^{\text{kR}}(\lambda)$ coefficients, $f(\lambda)$ can be decomposed into $C_k(\lambda)$ and $R_k(\lambda)$, respectively. The iterative procedure stops after a fixed number of decompositions ($L = 16$), or after the following stopping criterion (STC) is satisfied, i.e.: $\text{STC} = |E\{R_k^2(\lambda)\} - E\{R_{k-1}^2(\lambda)\}| < \epsilon, 1 \gg \epsilon > 0$. After the last iteration (L) the coherent part of the signal, Heart Sounds is composed by superposing the coherent parts derived at each iteration k , i.e.: $\text{HS}(\lambda) = \sum_{k=1}^L C_k(\lambda)$, while the remaining signal is the (Lung Sounds, i.e. $\text{LS}(\lambda) = R_L(\lambda)$). The filter separates heart sounds from lung sounds, only at locations of their presence, keeping unchanged the rest of the input signal. The implemented algorithm is outlined in TABLE II.

TABLE II
WT-ANC ALGORITHM

1. Initialization
 $X[\lambda], \lambda = 1 \dots N, N = 2048$
 F_{adj} : adjusting multiplicative factor
 m : number of WT scales, $1 \dots M, M = \log_2(N)$

3. Loop for each iteration process, $k = 1 \dots L, L = 8$ to 10
 Compute $MRD(f[\lambda])_{mscales} = WT^k[\lambda]$
 Save 2 copies of $WT^k[\lambda], WT^{kC}[\lambda]$ and $WT^{kR}[\lambda]$
 Loop for each wavelet scale, $j = 1 \dots M$
 Compute standard deviation, σ_j^k
 Compute threshold, $THR_j^k = \sigma_j^k * F_{adj}$
 Loop for the number of WT coefficients at each wavelet scale,
 $i = 1 \dots (N/2^j)$
 Compare $WT_j^k [i]$ and THR_j^k
 if $WT_j^k [i] < THR_j^k$ then
 $WT_j^{kC} [i] = 0$
 else
 $WT_j^{kR} [i] = 0$
 end loop i
 end loop j
 Compute $C_k[\lambda] = MRR(WT_j^{kC})_{mscales}$
 Compute $R_k[\lambda] = MRR(WT_j^{kR})_{mscales}$
 Compute criterion $STC = |E\{R_{k-1}^2[\lambda]\} - E\{R_k^2[\lambda]\}|$
 Compute STC and compare to ϵ
 if $STC \geq \epsilon$ then
 $f[\lambda] = R_k[\lambda]$
 else
 $k = L$ (end loop k)
 end loop k

5. Compute Pure Vesicular Sounds - PVS (Lung sounds)
 $PVS[\lambda] = R_1[\lambda]$.

3.3.3 Sensitivity Analysis of the WTC-ANC

A sensitivity analysis of the WT-ANC algorithm was performed, by changing various parameters, which are used in the algorithm. The parameters included the wavelet basis

function, the window size, the stopping criterion, the max number of iterations, and the F_{adj} parameter used to set the hard threshold for separation of the coefficients. Only one parameter setting was changed at a time, with unchanged parameters being set to recommended settings from the referenced papers [11] and [12] and or selected settings. Upon changing a parameter setting, a visual inspection was made of the time domain and PSD plots of the separated heart and lung signals. In addition, the beat detection algorithm was applied to the separated heart signal. Furthermore, the reference implementation data files provided by Dr. Hadjileontiadis, corresponding to the adjusting multiplicative constant, F_{adj} , settings of 3.0, 3.1, 3.2, 3.3, and 3.4, for separated heart and lung sounds were also used to show the sensitivity of this parameter for separating heart sound signals for input to the heartbeat detection and localization algorithm.

The input signal (“BreathingNormal.wav” as listed in Appendix A) of a subject exhibiting normal breathing was used for the sensitivity analysis WTC-ANC filter implementation. The results for default settings of wavelet basis function Daubechies10, adjusting multiplicative factor $F_{adj} = 3.0$, window length, $N = 2048$, max number of iterations $L = 10$, and stopping criterion threshold $\epsilon = 0.00001$ are shown in Fig. 5. All of the time domain representations in the sensitivity analysis chapter show a time domain in samples and a signal value range in millivolts. All of the PSD plots show a domain in frequency and a range in db/Hz. The results for the default configuration meet the defined acceptance criteria as previously described in Section 3.3.1 Heart and lung sounds separation techniques.

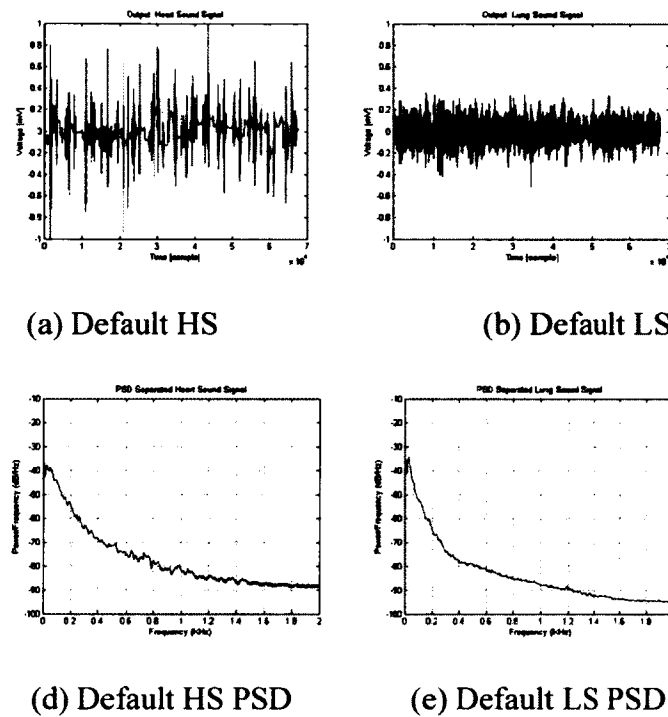


Fig. 5. Separation results for default WT-ANC parameters.

In the validation work by Hadjileontiadis and Panas [11] the various lengths of Daubechies wavelet basis functions from 2 to 20 were analyzed. The authors noted that there were not major differences resulting from the different length basis functions and they settled on the Daubechies basis function of length 8 coefficients. Gnitecki, Hossain, Pasterkamp, and Moussavi and Moussavi [12] also used this specific wavelet basis function. Various length Daubechies [38] wavelet basis functions, as well as functions from other families such as Haar, Symlets, Coiflets, BiorSplines, and DMeyer wavelets, were tested. The discrete Haar wavelet is a sequence of rescaled "square-shaped" functions and is advantageous for the analysis of signals with sudden transitions. Symlets, near symmetrical wavelets, were also developed by Daubechies [38] as an alternative to the Daubechies wavelet family. Another discrete wavelet family is the

Coiflets family, which was also designed by Daubechies [38]. Similar to the Daubechies wavelet family, these wavelets have scaling functions with vanishing moments.

However, the Coiflets wavelets are near symmetric. The BiorSplines family consists of biorthogonal spline wavelets. The results are presented in Fig. 6., Fig. 8, and TABLE III. Out of the Daubechies family, the wavelet with 10 coefficients performed the best for separating heart and lung sounds. The 8-coefficient wavelet was second. As can be seen in Fig. 6.a-b., some heart sound components are in the lung sound signal, and some lung sound components are present in the heart sound signal. The PSD plots shown in Fig. 6.c-d. support this assessment. The PSD of the heart sound signal has considerable power between 100 -200 Hz, where lung sounds usually occur. The rest of the Daubechies wavelets did not perform as well, per the acceptance criteria defined in Section 3.3.1 Heart and lung sounds separation techniques, as heart and lung sound components were present in both signals. Based on the results shown in Fig. 7. and Fig. 8., the performance of the other wavelet families is not acceptable . The results for the DMeyer wavelet, shown in Fig. 8.e-h., are the best, however, too many lung sound components are still present in the separated heart sound signal. The separation assessments and calculated for heart rates and first heart beat location are shown in TABLE III. It can be seen that incorrect heart rate calculations correlate with poor heart and lung sound separation.

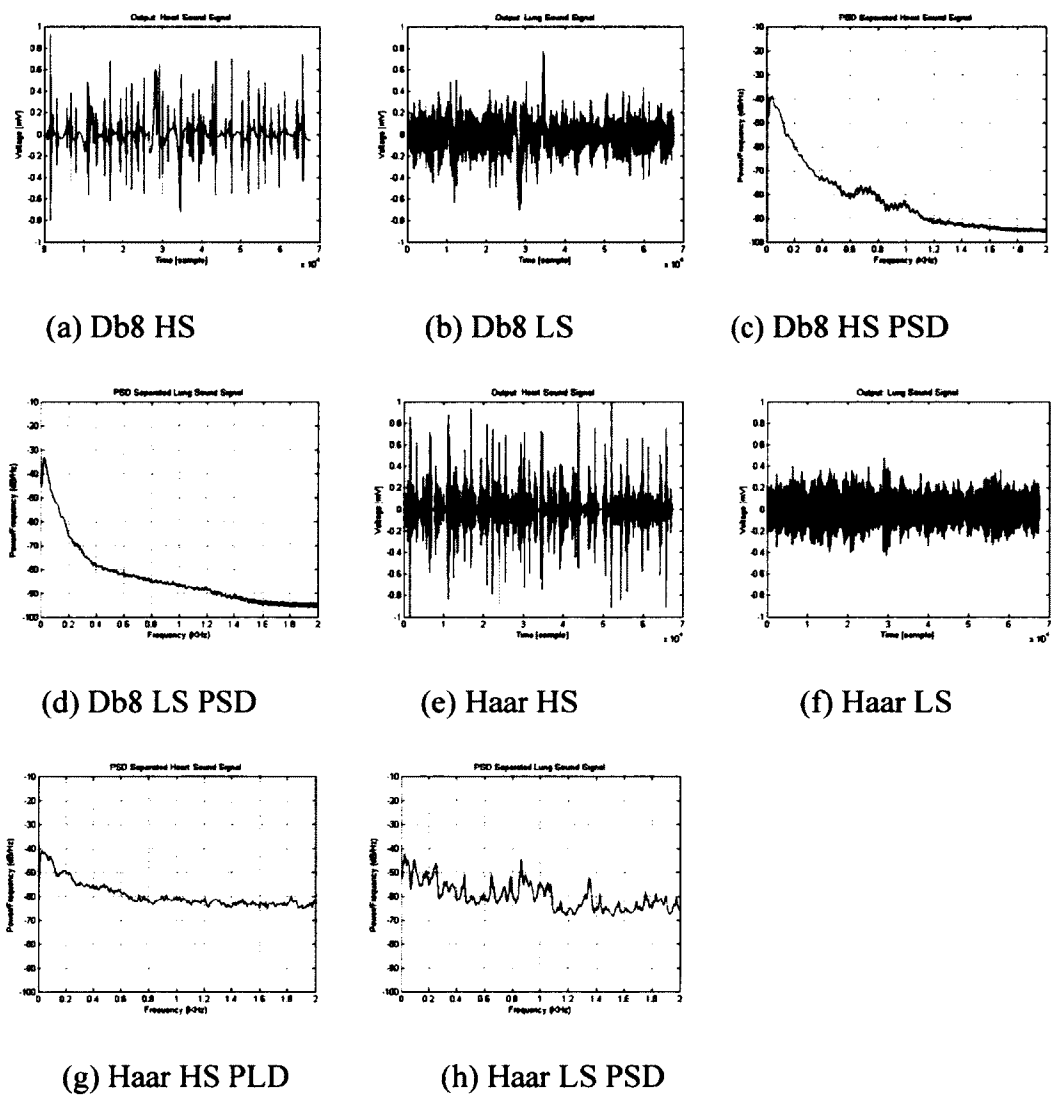
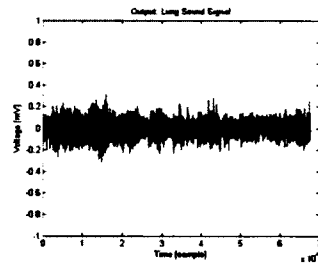
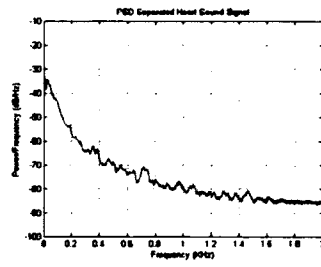


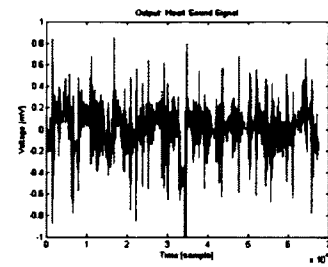
Fig. 6. Wavelet basis function analysis for Daubechies 8 and Haar.



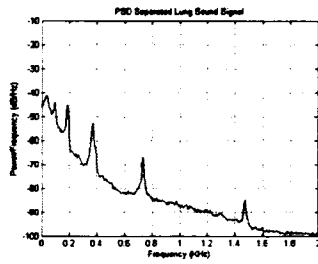
(a) Coif5 HS



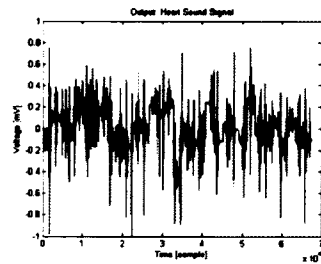
(b) Coif5 LS



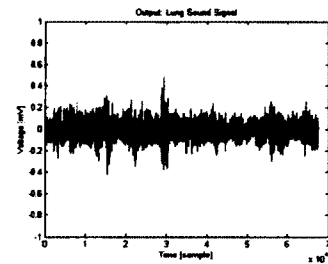
(c) Coif5 HS PSD



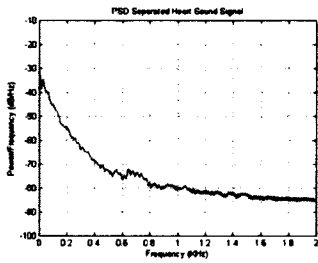
(d) Coif5 LS PSD



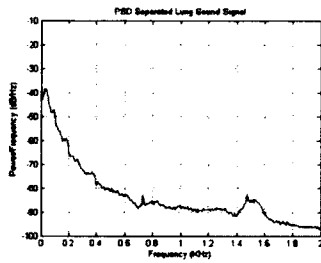
(e) Sym8 HS



(f) Sym8 LS

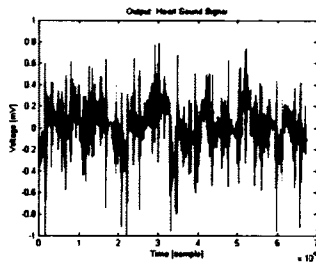


(g) Sym8 HS PSD

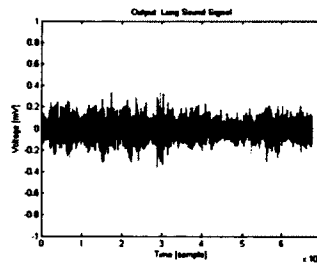


(h) Sym8 LS PSD

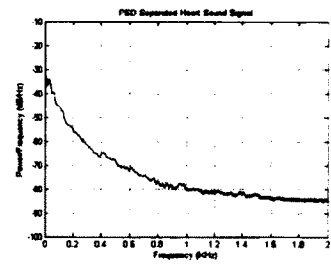
Fig. 7. Wavelet basis function analysis for Coief5 and Sym 8.



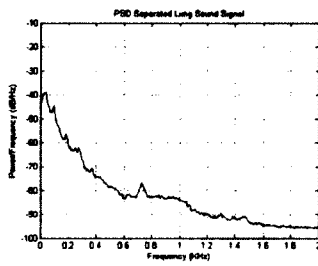
(a) Bior6.8 HS



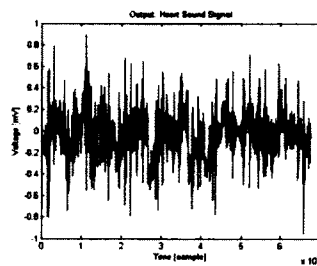
(b) Bior6.8 LS



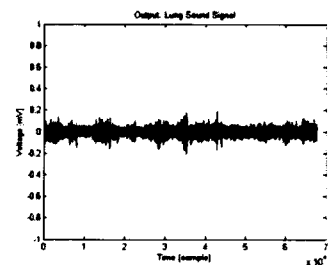
(c) Bior6.8 HS PSD



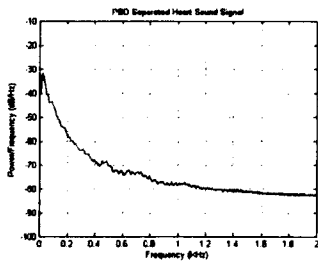
(d) Bior6.8 LS PSD



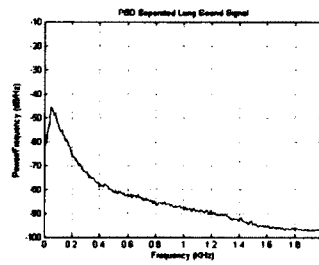
(e) DMeyer HS



(f) DMeyer LS



(g) DMeyer HS PSD



(h) DMeyer LS PSD

Fig. 8. Wavelet basis function analysis for BiorSplines 6.8 and DMeyer.

TABLE III
WTC-ANC SENSITIVITY ANALYSIS: WAVELET BASIS FUNCTION^a

Setting	HS/LS Separation Time Domain	HS/LS Separation PSD	Calculated HR (bpm)	First Beat Location (Sample #)
DB5	Poor	Poor	180.25	480
DB7	Poor	Poor	39.39	2832
DB9	Poor	Poor	32.23	3813
DB12	Poor	Poor	180.13	454
HAAR	Poor	Poor	183.75	1425
DMEY	Poor	Poor	65.40	442
BIOR6.8	Poor	Poor	179.76	1

^a $F_{adj} = 3.0$, $N = 2,048$, $L = 10$, $\epsilon = 0.00001$.

In the validation work by Hadjileontiadis and Panas [11] a window size, N , of 1,024 and 2,048 were used. These windows sizes as well as sizes of 512 and 4,096 were tested. The results are shown in Fig. 9, Fig. 10., and TABLE IV. Per the acceptance criteria defined in Section 3.3.1 Heart and lung sounds separation techniques, the window sizes of 512 (Fig. 9a-d.), 1,024 (Fig. 9e-h.), and 4,096 (Fig. 10e-f.), all had poor performance, since heart sound and lung sound components are present in both separated signals as seen in both the time domain and frequency domain representations. However, the window size of 2,048 (Fig. 10a-d.), performed well. The poor performance of the 1,024 window size was surprising, since it was one of two sized used in work by Hadjileontiadis and Panas [11].

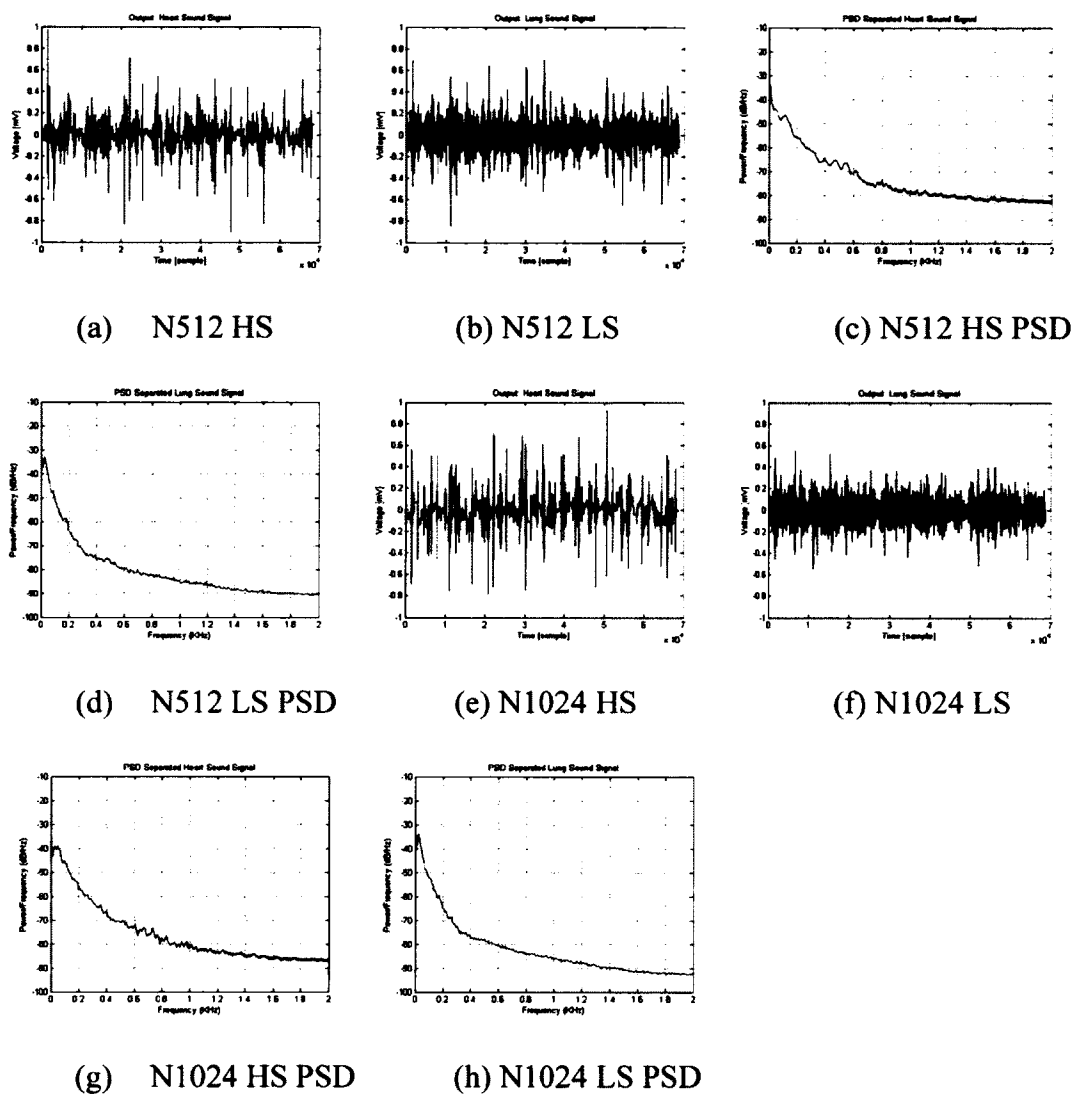
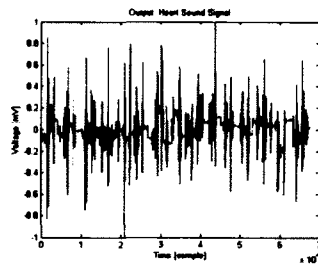
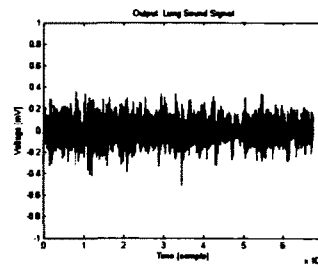


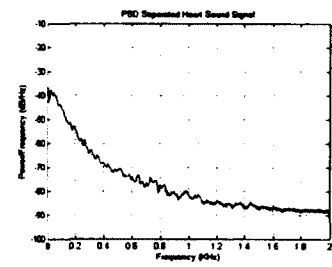
Fig. 9. WTC-ANC window size analysis for $N = 512$ and $N = 1,024$.



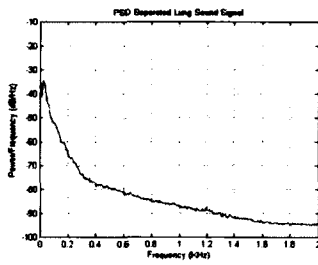
(a) N2048 HS



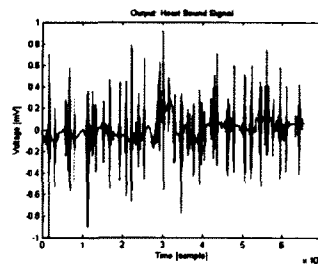
(b) N2048 LS



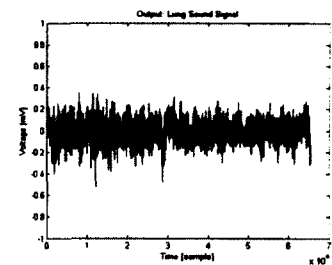
(c) N2048 HS PSD



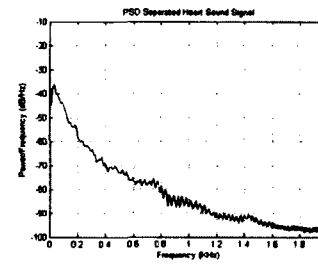
(d) N2048 LS PSD



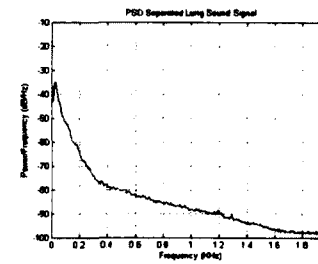
(e) N4096 HS



(f) N4096 LS



(g) N4096 HS PSD



(h) N4096 LS PSD

Fig. 10. WTC-ANC window size analysis for $N = 2,048$ and $N = 4,096$.

The separation assessments and calculated for heart rates and first heart beat location are shown in TABLE IV. It can be seen that a window size of 2,048 did also provide a signal conducive to correct heart rate calculations. The incorrect calculations for the window size of 4,096 are surprising, since the separation was very good.

TABLE IV
WT-ANC SENSITIVITY ANALYSIS: WINDOW SIZE (N)^a

Setting N	HS/LS Separation Time Domain	HS/LS Separation PSD	Calculated HR (bpm)	First Beat Location (Sample #)	Processing Efficiency (seconds)
512	Poor	Poor	156.39	621	20
4096	Very Good	Very Good	42.05	2497	3

^a Basis = DB10, $F_{adj} = 3.0$, $L = 10$, $\epsilon = 0.00001$.

Both Gnitekci, Hossain, Pasterkamp, and Moussavi [12] and Hadjileontiadis and Panas [11] used a stopping criterion threshold ϵ , of 0.00001. No other values were presented, however values of 0.000001, 0.0001, and 0.001 were also tested. The results are presented in Fig. 11, Fig. 12, and TABLE V. Per the acceptance criteria defined in Section 3.3.1 Heart and lung sounds separation techniques, the values of 0.000001 (Fig. 11e-h.), 0.0001 (Fig. 12a-d.), and 0.001 (Fig. 12e-f.), all had poor performance, since heart sound and lung sound components are present in both separated signals as seen in both the time domain and frequency domain representations. However, the stopping criterion threshold of 0.00001 (Fig. 11a-d.), also used by Hadjileontiadis and Panas [11], performed well.

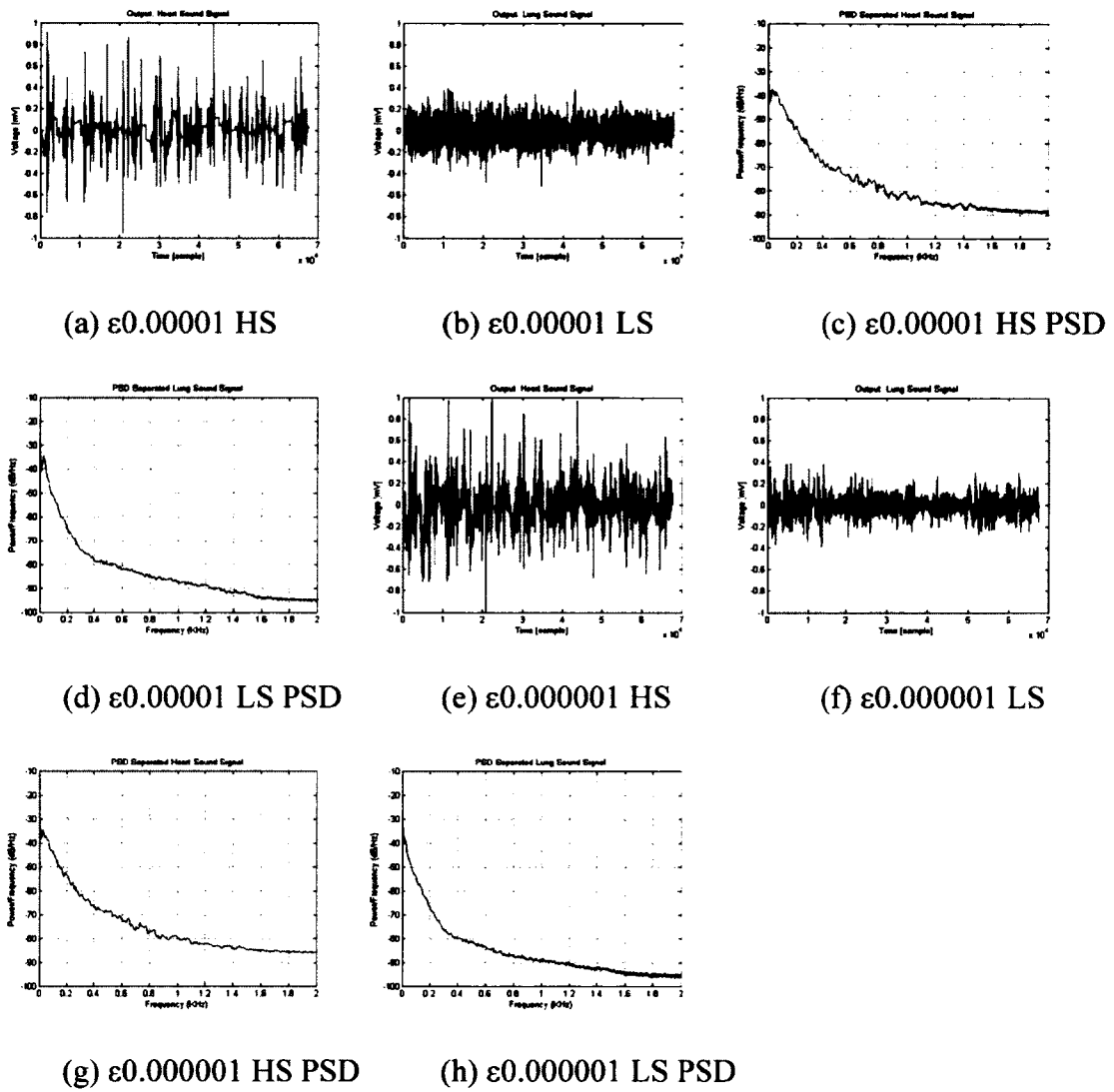


Fig. 11. WTC-ANC stopping threshold analysis for $\epsilon = 0.00001$ and $\epsilon = 0.000001$.

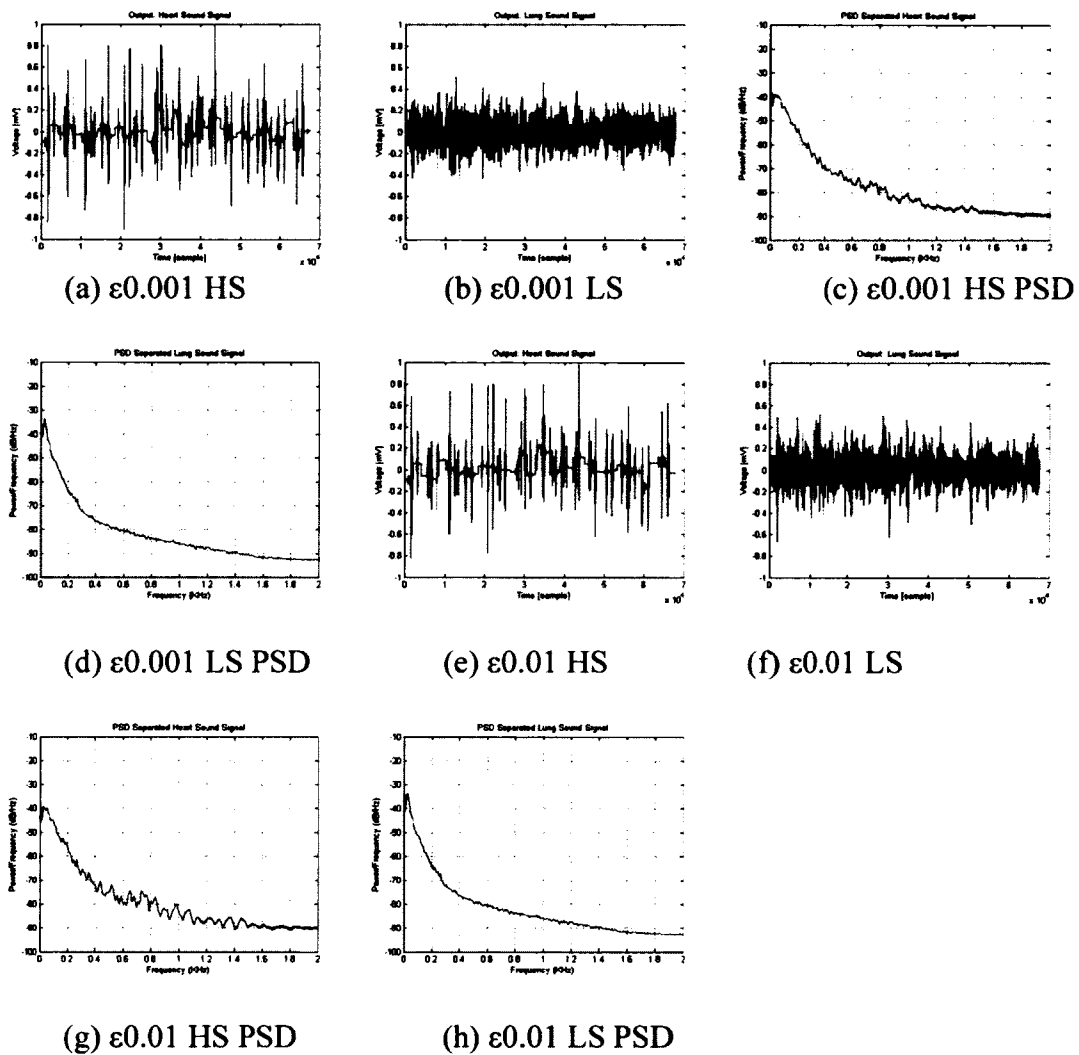


Fig. 12. WTC-ANC stopping threshold analysis for $\epsilon = 0.001$ and $\epsilon = 0.01$.

The separation assessments and calculated for heart rates and first heart beat location are shown in TABLE I. It can be seen that a stopping criterion threshold of 0.00001 resulted in a signal conducive to correct heart rate calculations. Even though the other values had acceptable heart rate calculations, their assessed separations are poor.

TABLE V
WT-ANC SENSITIVITY ANALYSIS: STOPPING CRITERION (ϵ)^a

Setting STC	HS/LS Separation Time Domain	HS/LS Separation PSD	Calculated HR (bpm)	First Beat Location (Sample #)	Processing Efficiency (seconds)
0.000001	Poor	Poor	182.11	1	20
0.001	Poor	Poor	58.77	246	2

^a Basis = DB10, $F_{adj} = 3.0$, $N = 2,048$, $L = 100$.

Hadjileontiadis and Panas used values of 5 - 8 for the max number of iterations, L , in their validation work presented in [11]. Gnitecki, Hossain, Pasterkamp, and Moussavi [12] recommended values of 8 – 10 in their qualitative analysis. These values as well as 4, 12, 14, 16, 18, 20, and 25 were tested. The results are presented in Fig. 13., Fig. 14., and TABLE VI. The separation assessments and calculated for heart rates and first heart beat location are shown in TABLE VI. It can be seen that maximum iterations of 10 and greater resulted in a signal conducive to correct heart rate calculations. These results are also seen in the time domain and frequency domain representations of the separated heart and lung sound signals. Per the acceptance criteria defined in Section 3.3.1 Heart and lung sounds separation techniques, the values $L = 4$ (Fig. 13a-d.), $L = 6$ (Fig. 13e-h.), and $L = 8$ (Fig. 14a-d.), all had poor performance, since heart sound and lung sound components are present in both separated signals as seen in both the time domain and frequency domain representations. The separation for $L = 8$ was acceptable as the presence of opposite sounds in each signal was minimal. However, the resulting

separated heart signal did not have a correct heart rate calculation. The value $L = 10$ was selected and its results were previously shown in Fig. 5.

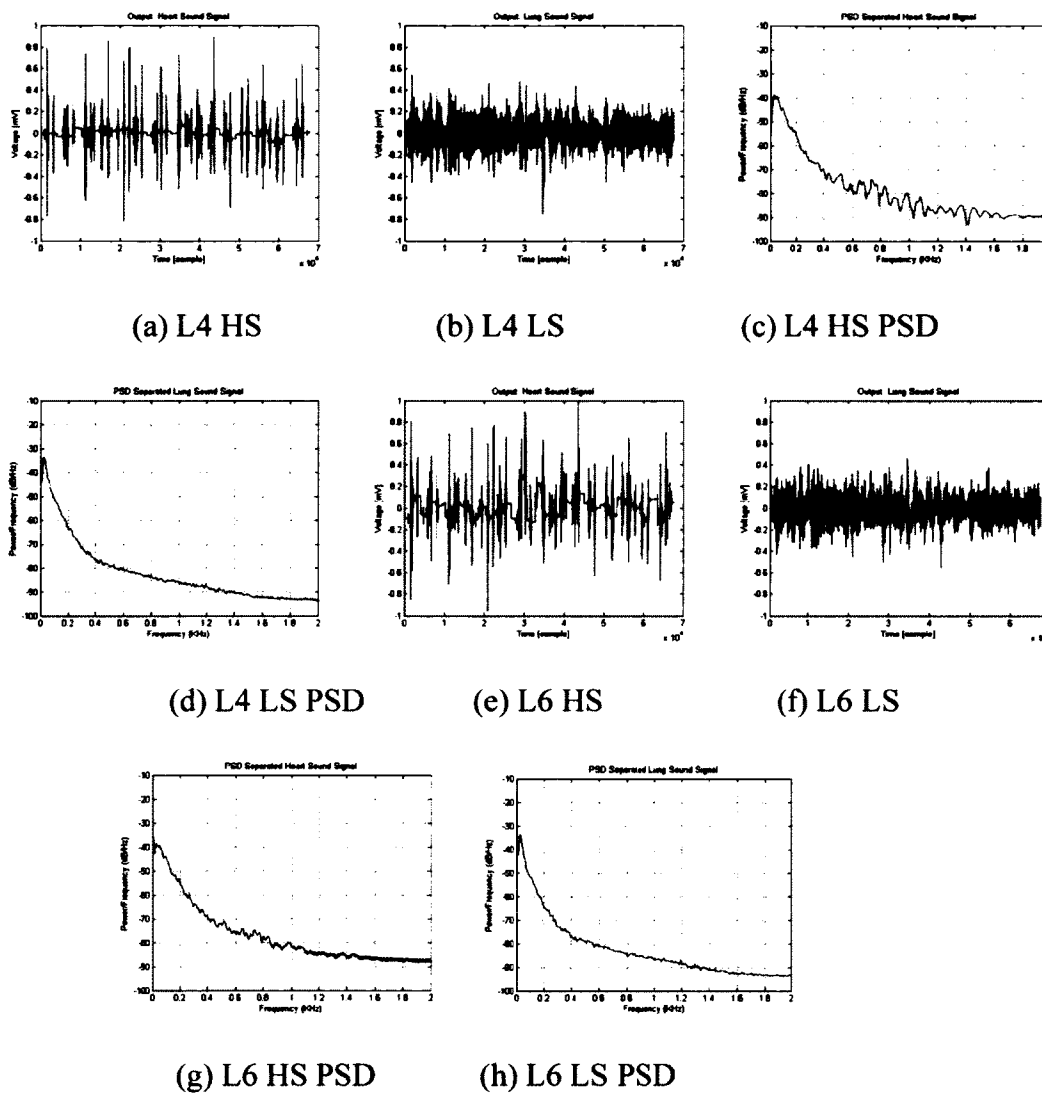
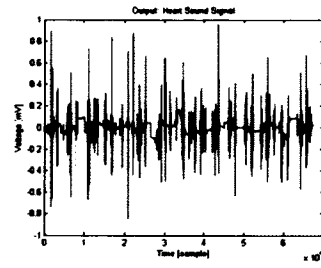
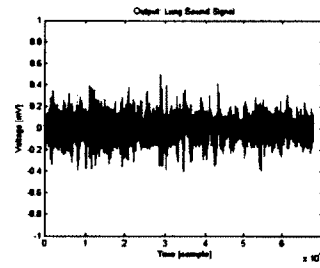


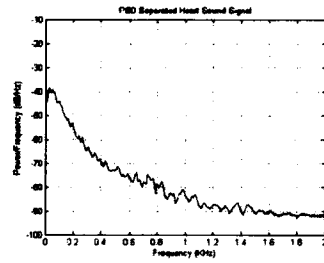
Fig. 13. WTC-ANC max iterations analysis for $L = 4$ and $L = 6$.



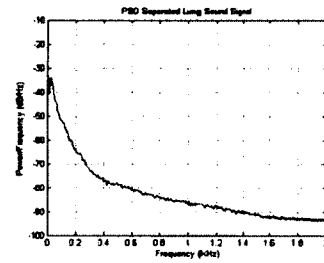
(a) L8 HS



(b) L8 LS



(c) L8 HS PSD



(d) L8 LS PSD

Fig. 14. WTC-ANC max iterations analysis for $L = 8$.

TABLE VI
WT-ANC SENSITIVITY ANALYSIS: MAX ITERATION (L)^a

Setting L	HS/LS Separation Time Domain	HS/LS Separation PSD	Calculated HR (bpm)	First Beat Location (Sample #)	Processing Efficiency (seconds)
6	Good	Good	58.47	236	3
10	Very Good	Very Good	58.78	247	5
14	Very Good	Very Good	58.79	247	5
18	Very Good	Very Good	58.81	4252	6
25	Very Good	Very Good	58.78	282	6

^a Basis = DB10, $F_{adj} = 3.0$, $N = 2,048$, $\epsilon = 0.00001$.

For the adjusting multiplicative constant, F_{adj} , Hadjileontiadis and Panas [11] settled on 3.0. They actually tested values from 2.0 to much greater than 3.0. Gnitecki, Hossain, Pasterkamp, and Moussavi [12] recommended a value of 3.0, but stated that values of 2.5 – 2.7 could be used, in their qualitative analysis. The values from 2.0 to 4.0 were tested. The results are presented in Fig. 15-16. and TABLE VII. The separation assessments and calculated for heart rates and first heart beat location are shown in TABLE VII. It can be seen that F_{adj} values of 3.0 and 3.0 had acceptable separation and were conducive to supporting an accurate heart rate calculation. F_{adj} of 3.2 did provide an acceptable separation, but the heart rate calculation of the separated heart sound signal is incorrect calculations. All other values of F_{adj} had unacceptable performance. These results are also seen in the time domain and frequency domain representations of the

separated heart and lung sound signals. As can be seen in Fig.15 and Fig. 16., F_{adj} values of 2.0 – 2.9 result in lung sound components being present in the heart sound signal. F_{adj} values greater than 3.3 result in heart sound components being present in the lung sound signal. The greater the F_{adj} value above 3.3 the more heart sound components are present, which is correct, since the F_{adj} is used in the hard thresholding calculation to separate wavelet transform coefficients.

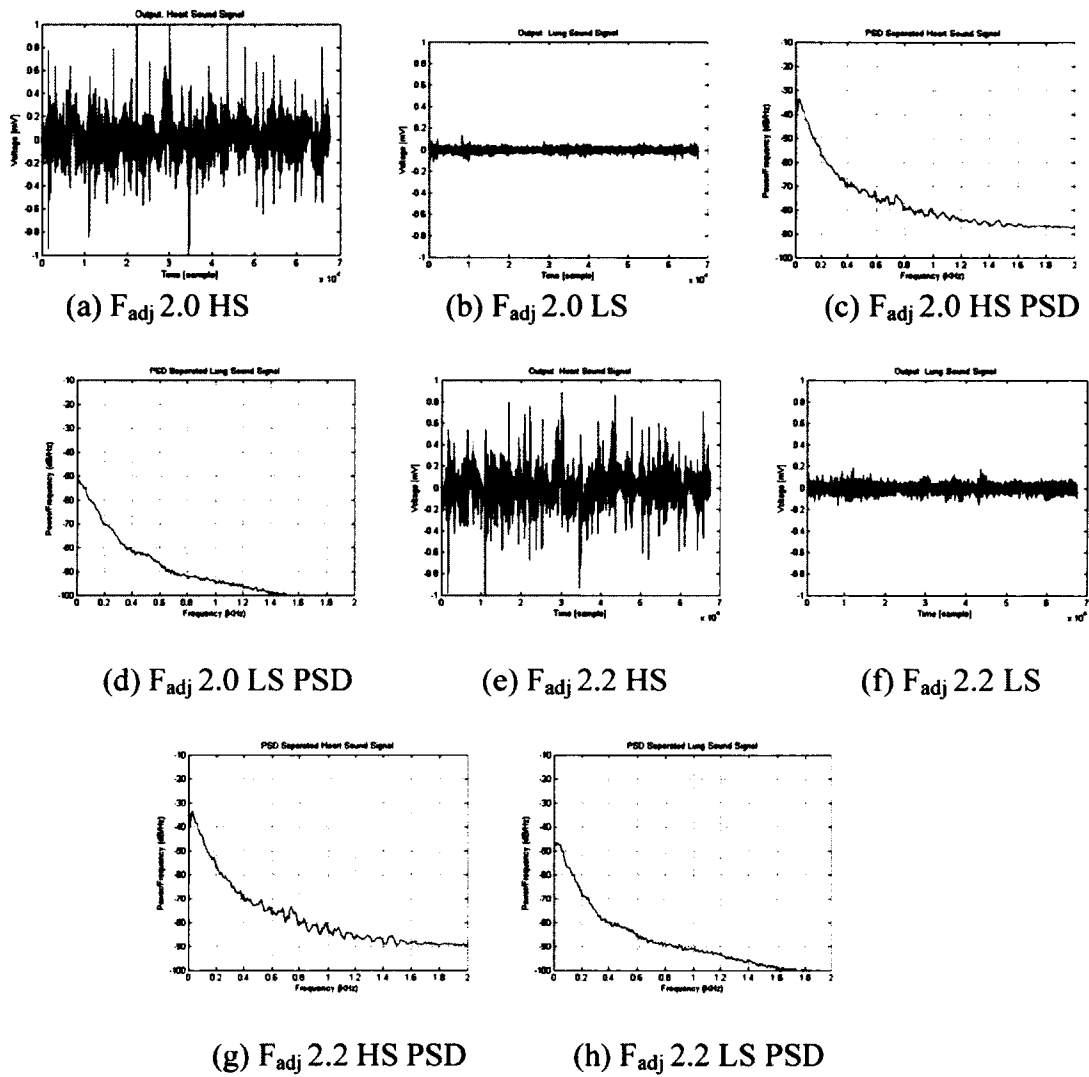


Fig. 15. WTC-ANC analysis for $F_{adj} = 2.0$ and $F_{adj} = 2.2$.

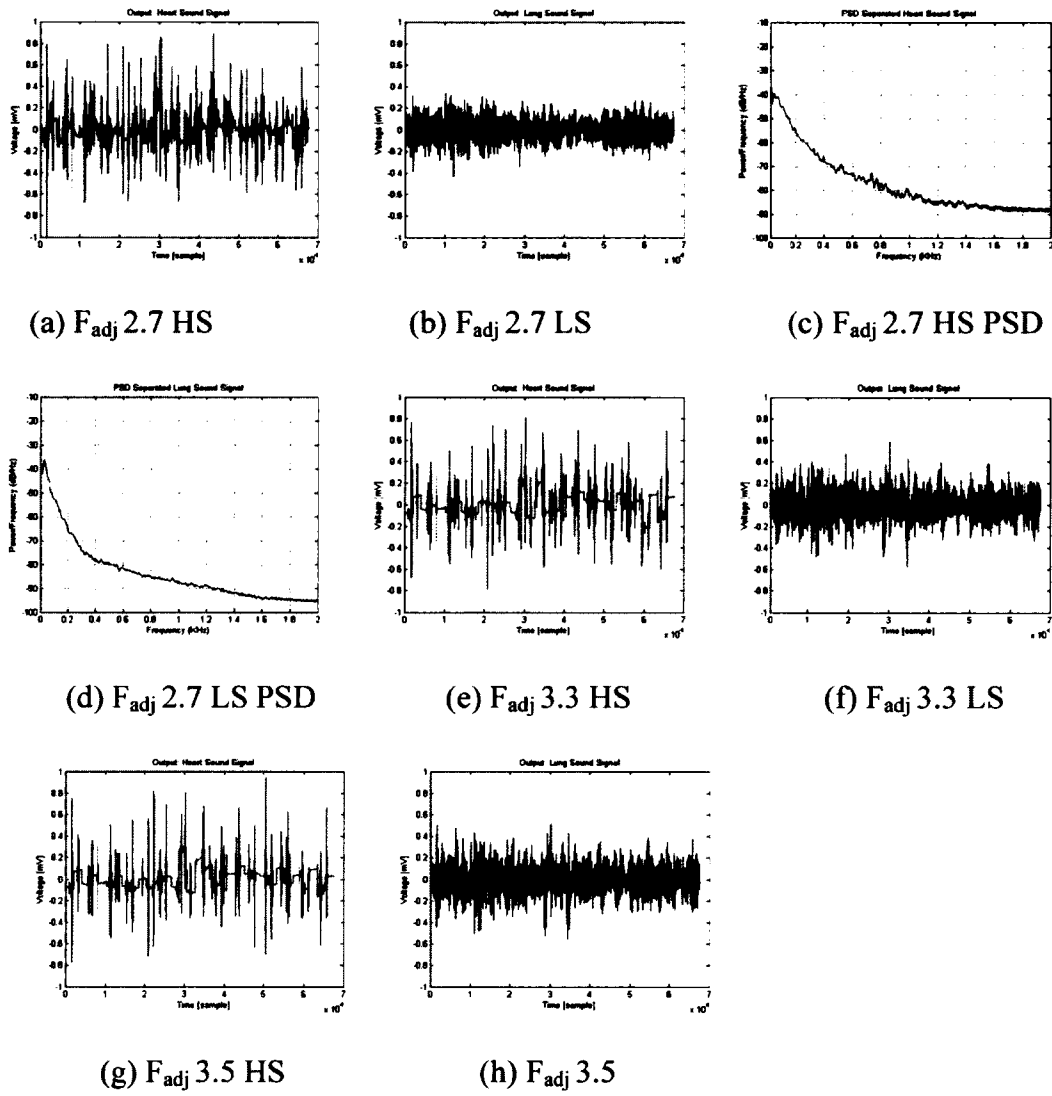


Fig. 16. WTC-ANC analysis for $F_{adj} = 2.7$, $F_{adj} = 3.3$, and $F_{adj} = 3.5$.

TABLE VII
WT-ANC SENSITIVITY ANALYSIS: F_{adj} ^a

Setting F_{adj}	HS/LS Separation Time Domain	HS/LS Separation PSD	Calculated HR (bpm)	First Beat Location (Sample #)
2.1	Poor	Poor	192.16	1286
2.3	Good	Good	58.67	4439
2.5	Good	Good	58.49	4454
2.7	Good	Good	183.75	720
2.9	Good	Good	58.73	4260
3.1	Very Good	Very Good	185.56	949
3.3	Good	Good	180.5	503
3.5	Poor	Poor	180.5	503
3.7	Poor	Poor	183.63	948
3.9	Poor	Poor	182.36	892

^a Basis = DB10, N = 2048, L = 10, ϵ = 0.00001

Based on the initial sensitivity analysis results, three runs with combined parameters were selected to assess whether a combination of parameters might improve some borderline acceptable parameters settings. For instance, the max iteration number was decreased in combination of F_{adj} settings to see if less separation iterations would preclude incorrect separations. Both attempts did not provide favorable results, as seen in TABLE VIII. In addition, an attempt was made to improve separation for a window size of 1,024 by using the better performing F_{adj} value of 3.4. This configuration also provided poor results.

TABLE VIII
WT-ANC SENSITIVITY ANALYSIS: COMBINATIONS^a

Settings	HS/LS Separation Time Domain	HS/LS Separation PSD	Calculated HR (bpm)	First Beat Location (Sample #)
$F_{adj} = 3.4$ $N = 1024$	Poor	Poor	49.94	1950

^a Defaults: Basis = DB10, $N = 2,048$, $L = 10$, $\epsilon = 0.00001$.

Lastly, heartbeat detection and localization algorithm was applied to four separated heart sound signals from by Dr. Hadjileontiadis' reference WT-ANC implementation to assess the sensitivity of the reference implementation on the F_{adj} parameter. The results are shown in TABLE IX. It can be seen that the reference implementation is very sensitive to the F_{adj} value, which correlates to the analysis of the presented implementation.

TABLE IX
WT-ANC SENSITIVITY ANALYSIS: FADJ OF REFERENCE IMPLEMENTATION

Setting	HS/LS Separation Time Domain	HS/LS Separation PSD	Calculated HR (bpm)	First Beat Location (Sample #)
3.1	Very Good	Very Good	94.95	2,113
3.3	Very Good	Very Good	93.77	2,162

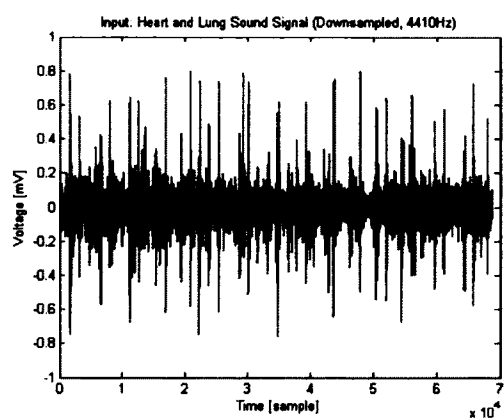
3.3.4 Results for WTC-ANC Heart and Lung Sounds Separation

From the results of the sensitivity analysis the parameters for the WT-ANC implementation were chosen as follows: Daubechies 10 wavelet basis function, F_{adj} setting of 3.4 and a maximum iteration value of 10, and STC of 0.0001. The results of applying this WTC-ANC filter configuration are discussed. Various reference signals as listed in Appendix A were utilized. The results for applying the WTC-ANC filters to the

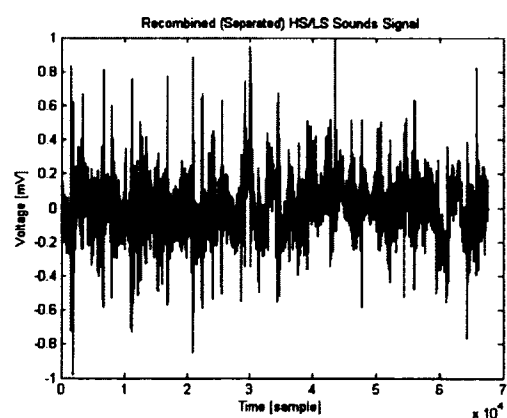
input signal (“BreathingNormal.wav” as listed in Appendix A) of a subject exhibiting normal breathing, are presented. The filter was applied to the input HS/LS signal; the separated HS and LS signals were acquired and then recombined for comparison to the original signal. Two comparisons of the original combined HS/LS signals; the separated HS and LS signals and the recombined HS/LS signals were made. The comparisons included 1) visually in the time domain and 2) the power spectral density (PSD).

The time domain and PSD results of applying the WTC-ANC filter are shown in Fig. 17. and Fig. 18. Each plot in Fig. 10. contains a 15.5-second signal with time domain in seconds and a signal value range in millivolts. Fig. 17. shows the time domain results of the WT-ANC filter separated signals. As can be seen, the down sampled HSLS input signal (Fig. 17a.) and recombined HSLS signal (Fig. 17b.) look comparable which shows that the original signal can be adequately reconstructed from the separated HS and LS signals, and that the filtering did not filter out or lose portions of the input signal. Fig. 17c. shows the separated HS signal and Fig. 17d. shows the separated LS signal.

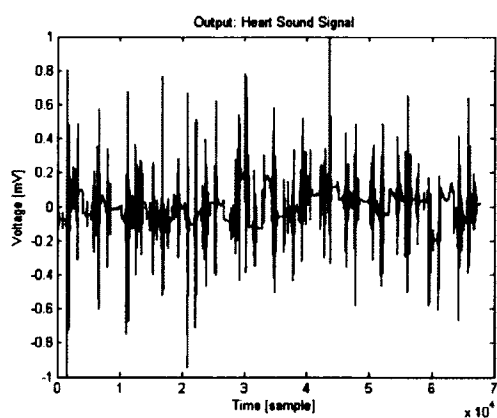
Visually, it can be seen that the heart and lung sounds are separated into their respective signals. Most likely, this is due to the inherent nature of the wavelet transform, which is very good at separating stationary and non-stationary portions of a signal. The algorithm peels the lung sounds into layers, reveals their coherent structure, and serves as a true separation tool of the non-stationary part of the signal [17].



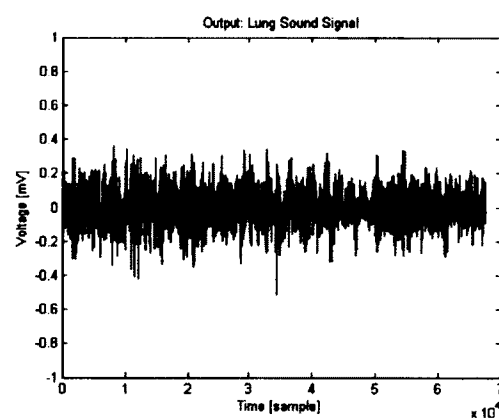
(a) Downsampled HSLs



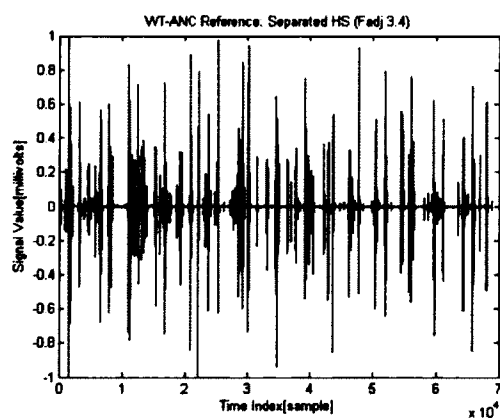
(b) Recombined HSLs



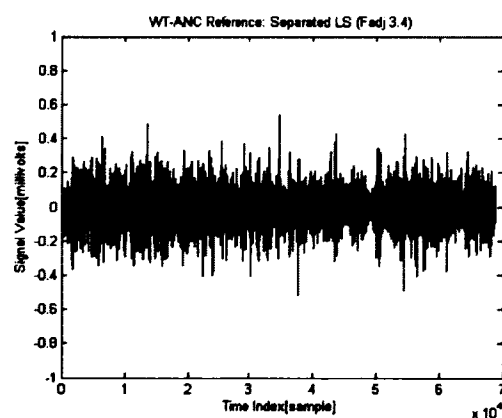
(c) Separated HS



(d) Separated LS



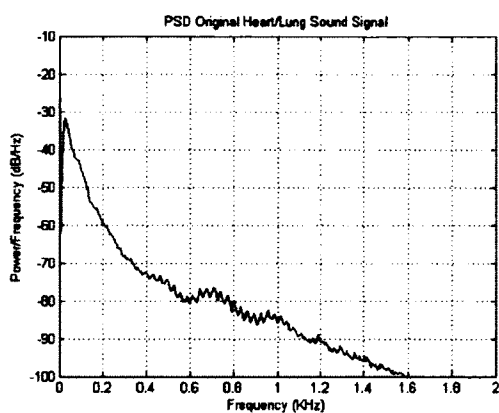
(e) Reference Separated HS



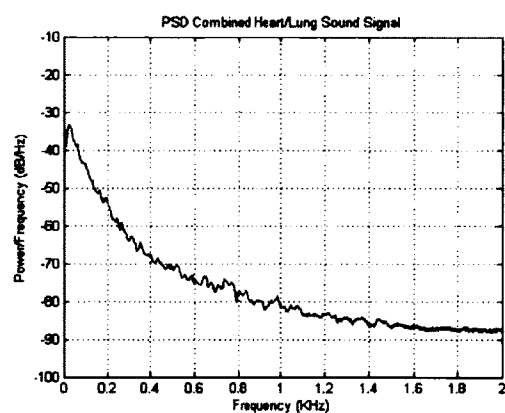
(f) Reference Separated (LS)

Fig. 17. WTC-ANC filter separated signals.

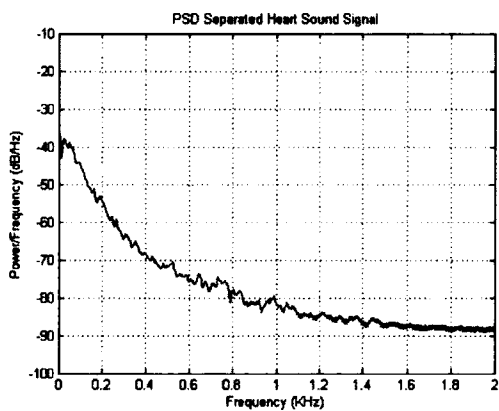
The comparison in Fig. 18. shows the calculated PSD of the original, separated and recombined signals of the WT-ANC. As can be seen in Fig. 18a. and Fig. 18b. the PSD of the recombined HSLs signal is comparable to that of the original HSLs signal. In both signals, the majority of the power is present at the lower frequencies, which is in line with the nature of both HS and LS. These PSD of the recombined HSLs signal is also comparable to that of the RLS Filter results. Fig. 18c. and Fig. 18d. show the PSD of the separated HS and LS signals. Both show that the majority of the power is also at the lower frequencies. Note that the PSD of the separated LS signal shows the peak, which contributes to same peak in the combined HSLs. These results better match the characteristics of both HS and LS where the LS has more overall power in the frequencies where both sounds are present.



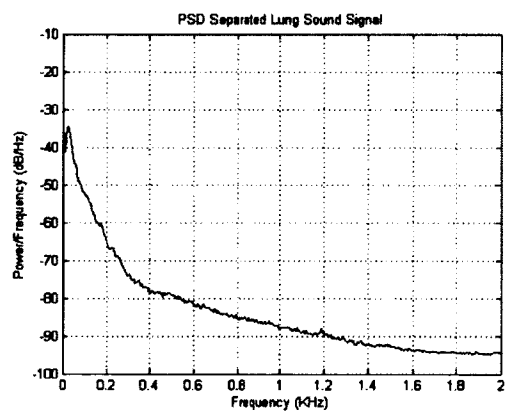
(a) Original HSLS



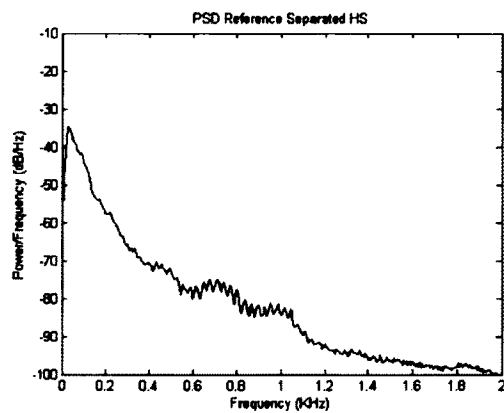
(b) Recombined HSLS



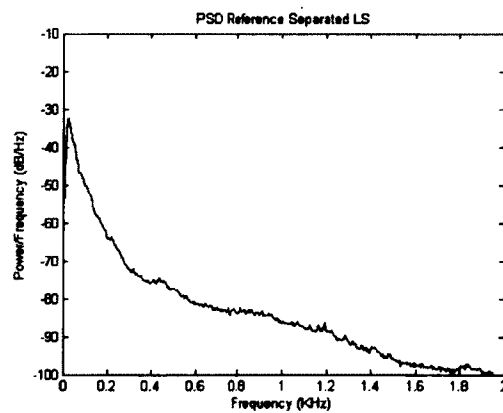
(c) Separated HS



(d) Separated (LS)



(c) Reference Separated HS



(d) Reference Separated (LS)

Fig. 18. WTC-ANC filter PSD comparison.

In addition, a comparison of the results of the implementation of the WTC-ANC filter with results from a reference implementation was conducted. The reference implementation was a custom WT-ANC filter, developed by Dr. Hadjileontiadis, as presented in his published papers [11], [15]. An input sound file, (“BreathingNormal.wav” as listed in Appendix A) recorded from the pulmonic auscultation site of a patient exhibiting normal breathing, was provided to Dr. Hadjileontiadis. Dr. Hadjileontiadis applied his custom implementation of the WT-ANC filter to the sound file and provided the results corresponding to using a F_{adj} parameter setting for 3.0, 3.1, 3.2, 3.3, and 3.4. The results of my implementation utilizing the Daubechies 10 wavelet basis function, a F_{adj} setting of 3.4 and a maximum iteration value of 10 are comparable to those of Dr. Hadjileontiadis for each of the F_{adj} parameter settings. The time domain and PSD results for the reference implementation for the F_{adj} setting of 3.4 are provided in Fig. 17e. and Fig.18f., and Fig.18e. and Fig.18f., respectively. The presented separated heart sound signal as shown in Fig. 17c. and the separated heart sound signal from the reference implementation in Fig. 17e. are comparable. It can be seen that the amplitude of the presented filtered signal has been reduced slightly more than that of the reference implementation. The separated lung sounds of both filters as shown in Fig. 17d. and Fig. 17f. are also comparable with neither including visually noticeable heart sound components. The PSD of the separated heart sounds of both implementations are shown in Fig. 18c. and Fig 18e. are comparable with similar trends and max power being present well below 150 Hz. The max PSD of the presented filter is slightly lower than that of the reference filter, but still comparable at

approximately -38 dB/Hz vs approximately -34 db/Hz. The PSD of the separated lung sounds of both implementations are shown in Fig. 18d. and Fig 18f. are comparable with similar trends and max power being present well below 150 Hz.

Lastly, the heartbeat detection and localization algorithm was applied to both the presented WT-ANC implementation and the reference implementation. The results are shown in TABLE X. A heart rate of 59.57 bpm and location of the first heart beat of sample 697 were calculated for the presented WTC-ANC implementation, while a heart rate of 60.51 bpm and location of the first heartbeat of sample 586 were calculated for the reference implementation. The heart rate and first beat location of the input signal are estimated at 60 bpm, and sample 700, respectively. The results are very comparable. The minor differences are attributed to the difference in the Wavelet Transform libraries provided in MatLab and those included in the custom implementation of the reference WT-ANC filter. This assumption is supported by the fact that Dr. Hadjileontiadis recognized general limitations of the wavelet libraries included in MatLab, which led him to develop his own wavelet libraries and finely tuned WT-ANC implementation.

TABLE X
COMPARISON OF HEARTBEAT DETECTION AND LOCALIZATION OF
IMPLEMENTATION AND REFERENCE SEPARATED HEART SOUND SIGNALS

BreathingNormally Signal	Heart Rate (bpm)	First Beat Location (Sample #)
Reference WTC_ANC Separated HS	60.51	586

^a Visual estimation from ECG signal plot. ^b Visual estimation from sound signal plot

3.4 Heartbeat Detection and Localization

To perform the Heart Signal Analysis, specifically detecting and localizing the heartbeats in the heart sound signal, tempo and beat estimation techniques were utilized to identify heart rate and beat. The well known tempo and beat detection algorithm of Eric Scheirer [5], was implemented to fulfill this requirement. Scheirer presented his tempo and beat detection algorithm to the community back in 1998. Since then, many researchers have continued Scheirer's work and have made possible improvements to his work. However, it was decided to utilize Scheirer's original algorithm, due to the absence of some of the researchers' assumptions, which were previously discussed. The heartbeat detection and localization algorithm, shown in Fig. 19., is implemented in MatLab.

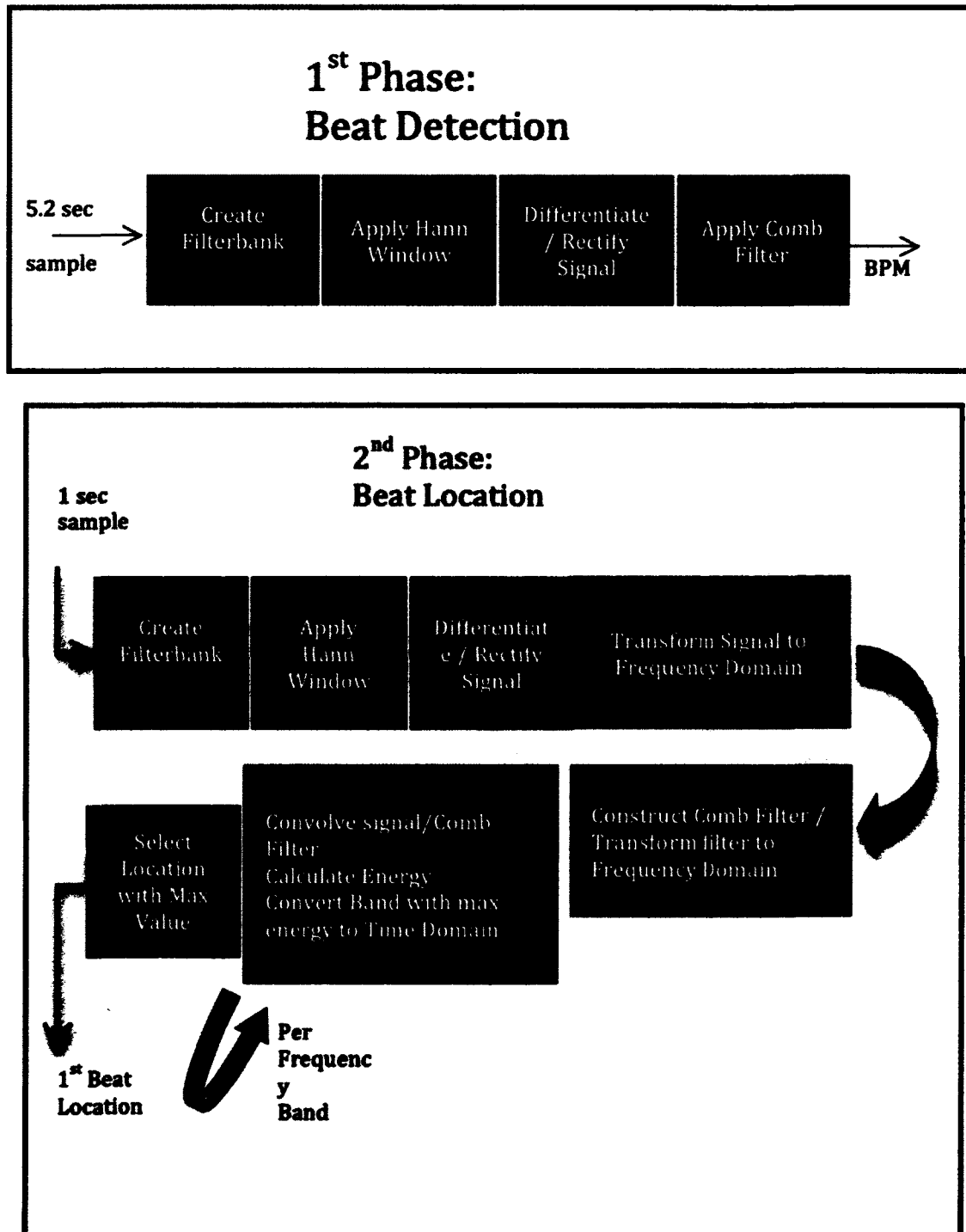


Fig. 19. Heartbeat detection and localization algorithm.

The algorithm is implemented in two phases. The first phase focuses on determining the heart rate. The second phase of the algorithm encompasses detecting the first location of the heartbeats. From the identified location of the first heartbeat and the calculated heart rate, the locations of successive heartbeats can be calculated. Both phases of the algorithm utilize a filter bank with the following frequency bands (in Hertz): 0 - 40, 40 - 80, 80 - 160, 160 - 320, and 320 - 640. These frequency bands were selected as being adequate for detecting the human heartbeat, which has an average of 72 beats per minute (bpm). The algorithm is applied to a 5.2 second representative sample taken from the middle portion of the signal data. The time domain sample signal is divided into individual frequency bands as defined for the filter bank. It is noted that the first sample (the dc component) is set to zero.

The first step in the heart rate detection is to apply the filter bank to the representative sample of the signal. The frequency domain output of the filter bank is shown in Fig. 20. The next step in the process is to apply a half-Hann window function to the frequency bands. For each frequency band, the signal is transformed to the time domain, full-wave rectified, transformed back to the frequency domain, convolved with a 200 millisecond half-hann window, and finally transformed back to the time domain. The output of the hann window is shown in Fig. 21. After the Hann window function is applied, the next step in the algorithm is a differentiation and rectification. A half-wave rectification, based on positive differences of adjacent samples, is applied to the signal in the time domain. The intermediate results of this step are shown in Fig. 22., which has a time domain in samples and an amplitude range in millivolts. Again, the different colors represent the six frequency bands.

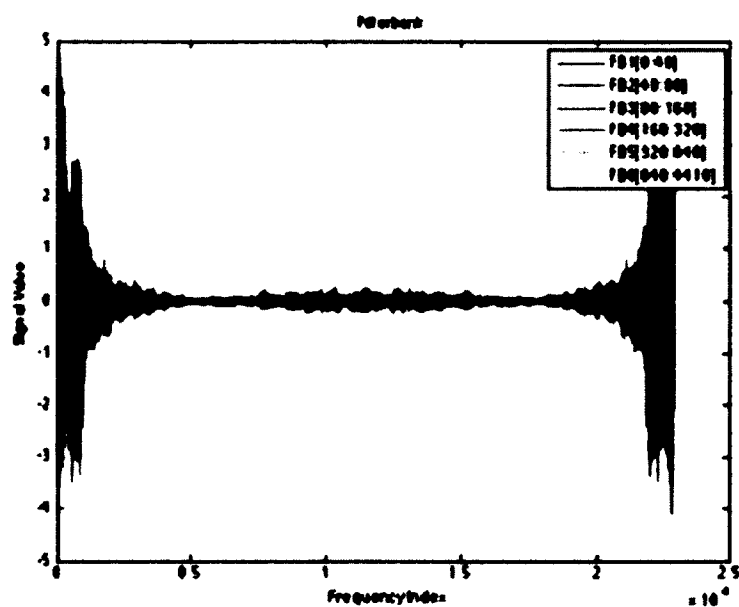


Fig. 20. Tempo and beat detection filter bank.

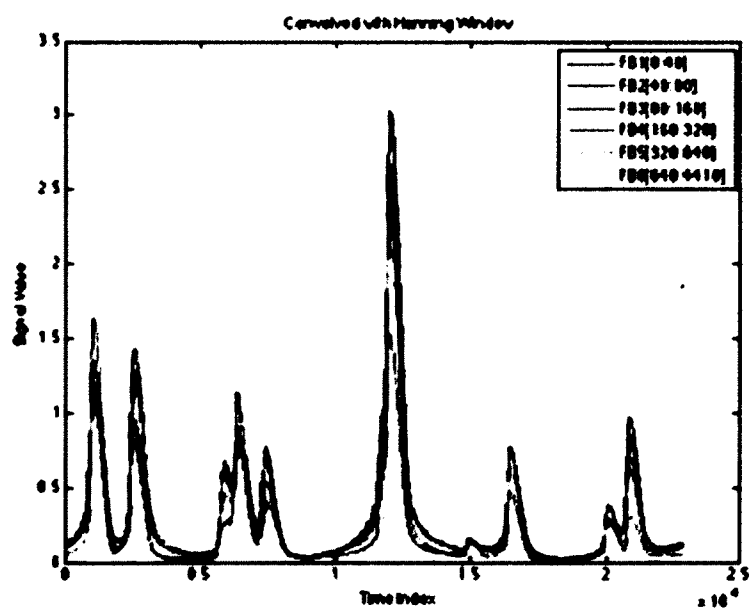


Fig. 21. Tempo and beat detection Hann window convolved signal.

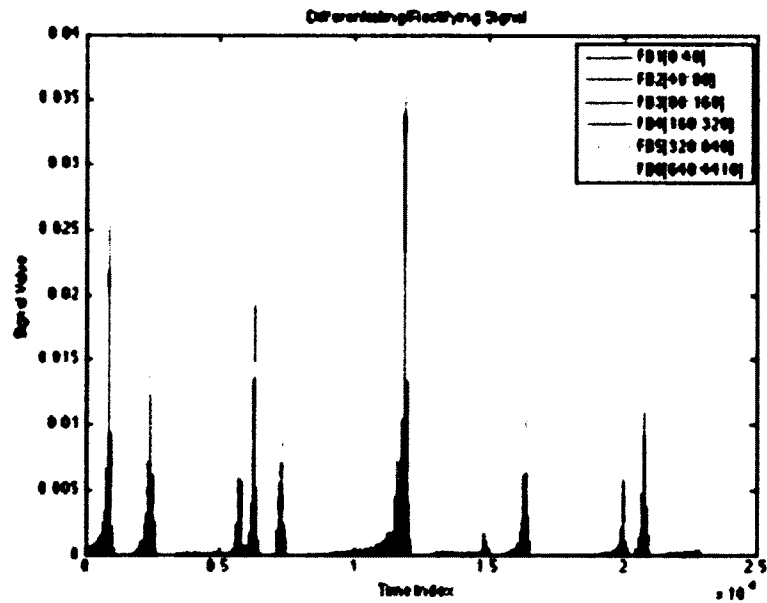


Fig. 22. Tempo and beat detection differentiated and rectified signal.

The final step in the heart rate detection phase of the algorithm is to iteratively apply a 3-pulse comb filter to the signal via a frequency domain convolution. The filter scans through a frequency range to determine the tempo, measured in beats per min, of the signal. The parameters, for each iteration, are shown in TABLE XI. The calculated tempo from each scan is used for the frequency limits for the next application of the filter to narrow down the actual BPM.

TABLE XI
BEAT DETECTION COMB FILTER PARAMETERS

Iteration	Num Pulses	#Bands	Fs (KHz)	Step	Min Freq	Max Freq	Output
2	3	6	44.1	0.5	$F1 - 2$	$F1 + 2$	F2
4	3	6	44.1	0.01	$F3 + 0.1$	$F3 + 0.1$	BPM

The first iteration scans the frequency range from 30 to 240 Hz. These values were selected to include the typical heart rate of a human being, adult or child. The output of the scan is the frequency with the maximum energy, the squared value of the convolution output. The selected frequency is then used as the basis of the minimum and maximum frequency limits for the next iteration, as shown in TABLE XI. The step sizes are predetermined. Four iterations are performed with the resolution of the final iteration set to 0.01 Hz. The output of the comb filter is the heart rate measured in BPM, and completes the first phase of the algorithm.

As shown in Fig. 19., the second phase of the heartbeat detection and localization algorithm encompasses detecting the first location of the heartbeats. From the identified location of the first heartbeat and the calculated heart rate, the locations of successive heartbeats can be calculated. The process to determine the heartbeat locations is very similar to the process used to calculate the heart rate. A one second representative signal is taken from the beginning of the separated heart sound signal. The filter bank is created, the half-hann window function is applied, a differentiation rectification process is applied, and finally, a three-pulse comb filter is applied to the signal via a frequency domain convolution. The frequency band with the maximum energy is selected, converted back to the time domain, and the sample with the maximum value is identified

as the first location of the heartbeat.

3.5 Substitution of Pathology

Once the heart and lung sound signals are separated, pathology including an abnormal heart sound or lung sound characteristic is added to the signal. Selected pathologies included a heart murmur, a crackle, and an asthma wheeze. The procedure for pathology substitution is shown in TABLE XII.

TABLE XII
PATHOLOGY SUBSTITUTION PROCEDURE

Step	Description
2	Apply heartbeat detection and localization to the reference pathology heart sounds signal.
4	Apply heartbeat detection and localization to the adjusted signal to verify the heart rate and to identify the first location of the heartbeat.
6	Shift and zero pad adjusted pathology signal by n samples.

The majority of the focus was on adding heart pathology as this included utilizing the beat and tempo detection algorithm as described in Section 3.4 Heartbeat detection and localization. When adding a heart abnormality sound signal, the heartbeat detection and localization algorithm is applied to both the separated heart sound signal (input) and the reference signal containing the pathology. The heart rates are compared, and if the difference in rates is greater or equal to two bpm, then the heart pathology signal is adjusted to match the heart rate of the separated heart sound signal (input). The sampling

rate is used to determine the number of samples to add to decrease the rate or remove to increase the rate.

After the pathology signal is modified to match the heart rate of the input heart sound signal, the heartbeat detection and localization algorithm is applied to the adjusted signal to verify the heart rate and to identify the first location of the heartbeat. The first location is compared to that of the input heart sound signal, and the adjusted pathology signal is shifted and zero padded n number of samples, where n equals the difference in sample number of the beginning of the first beat of each signal. No other adjustments are required as the signals should be comparable. Since the first beats have been lined up and the heart rates are closely matched, the successive heartbeats are also in sync. This does assume that the heart rates are constant throughout the signal. This assumption is acceptable since the objective is not to exactly match the input heart sound signal, but to combine a pathology signal with similar characteristics to the original separated lung sound to be presented back to the listener, i.e. medical student. When substituting lung pathology, the heartbeat detection and localization algorithm is not needed, as neither the heart sound signal nor the pathology lung sound signal are modified before being combined as described in Section 3.6 Heart sounds/lung sounds signal re-combination.

3.6 Heart Sounds/Lung Sounds Signal Re-combination

After the modification of the heart sound signal, the signal is recombined with the lung only sound signal. Basic, standard digital signaling processing techniques were used. Basically the heart sound signal and the lung sound signal are converted to the frequency domain, added together and then transformed back to the time domain using FFTs and IFFTs.

3.7 Output of Modified Heart/Lung Sounds Signal

Output files include the separated heart and lung sound signals, the modified heart or lung sound signal, and either the combined modified heart sound signal with the original lung sound signal or the original heart sound signal with the substituted lung sound signal. All output files are provided in the WAV format.

CHAPTER 4

VALIDATION RESULTS

This chapter discusses the validation results performed during the study. As previously stated, the objective of this research was to develop an innovative, accurate and efficient model of abnormal heart sounds and lung sounds that will support the real-time application of augmenting medical equipment with pathological sounds to be used with standardized patients to improve the training of medical students. Accuracy, realism and efficiency were the focus of the model development. Input and reference sound data files were acquired from medical staff. Documentation for the sound files was provided. The documentation included detailed descriptions of how the signals were recorded, including electronic settings of the electronic stethoscope. A qualitative assessment of the modified heart/lung sounds signals and a quantitative analysis using simulated signals as input into the heartbeat detection and localization, pathology substitution, and heart sounds/lung sounds signal re-combination portions of the model were performed. The qualitative portion of the validation included an auditory assessment of the signals by subject matter experts, experienced in training medical students. The quantitative portion of the validation involved creating a set of simulated heart and lungs signals to use to validate the model. The signal separation and signal modification portions of the model were applied separately to the simulated data set to validate the separate parts of the model. Then both parts of the model were applied in sequence with the output from the signal separation portion being used as input to the signal modification portion, to validate the complete model.

4.1 Qualitative Results

A qualitative assessment was performed. The assessment, similar to the qualitative analysis conducted by Gnitecki, Hossain, Pasterkamp, and Moussavi [12], involved the analysis of the modified heart/lung sounds signals, both visually and through auditory analysis of subject matter experts (SMEs) in the field of pathological sounds. Qualitative experts, who conducted analysis on various references and modified signals, conducted the assessment. Old Dominion University experts in signal processing and heart/lung sound signals conducted a visual inspection of the signal set. Medical staff, experienced in training medical students, from the Eastern Virginia Medical School (EVMS) conducted an auditory assessment of the signals. The assessment signal set contained, original heart sounds and lung sound signals, pathology heart and lung sound signals, combined (without heart sound adjustment) original and pathological signals, and combined (adjusted heart sound) original and pathological signals.

The data set of model output combination files was organized into various directories with titles corresponding to the combinations of heart sounds and lung sounds. The files are organized by combinations of “Pathology” and “Normal” signals, or just “Normal” signals, and with or without adjusting the HS signal to the Normal Breathing HS as a reference. The directory organization is shown in TABLE XIII.

TABLE XIII DATA SET DESCRIPTION

ID	Data Set Name	Hearts Sounds	Lung Sounds
DS2	HS NORMAL adjustment combined with LS PATHOLOGY	Middle Normal Tricuspid Normal (Adjusted)	Asthma, Crackles, Normal Tracheal
DS4	HS NORMAL no adjustment combined with LS PATHOLOGY	Aortic, Middle, Mitral, Normal, Pulmonic, Tricuspid	Asthma
DS6	HS PATHOLOGY no adjustment combined with LS NORMAL	Ejection Murmur	Aortic, Middle, Mitral, Normal, Pulmonic, Tricuspid

“The HS_NORMAL_adjustment_combined_with_LS_NORMAL” set contains various combinations of adjusted, separated heart sound signals from the normal breathing with middle stethoscope gain and tricuspid area normal breathing data files with separated lung sounds from the normal breathing aortic, mitral, pulmonic, and tricuspid chest areas, as well as normal breathing lung sound files with middle stethoscope gain.

The “HS_NORMAL_adjustment_combined_with_LS_PATHOLOGY” set contains various combinations of adjusted, separated heart sound signals from the normal breathing with middle stethoscope gain and tricuspid area normal breathing data files with lung pathology sound files containing asthma, crackle, or tracheal sounds.

The “HS_NORMAL_no_adjustment_combined_with_LS_NORMAL” set contains various combinations of separated, without adjustment, heart sound signals from the normal breathing with middle stethoscope gain and tricuspid area normal breathing data

files with separated lung sounds from the normal breathing aortic, mitral, pulmonic, and tricuspid chest areas, as well as normal breathing lung sound files with middle stethoscope gain.

The “HS_NORMAL_no_adjustment_combined_woth_LS_PATHOLOGY” set contains various combinations of separated, without adjustment, heart sound signals from the normal breathing with middle stethoscope gain and tricuspid area normal breathing data files with separated lung sounds from the normal breathing aortic, mitral, pulmonic, and tricuspid chest areas, as well as normal breathing lung sound files with middle stethoscope gain.

The “HS_PATHOLOGY_adjustment_combined_with_LS_NORMAL” set contains various combinations of an adjusted heart pathology, heart murmur, sound signal with separated lung sounds from the normal breathing aortic, mitral, pulmonic, and tricuspid chest areas, as well as normal breathing lung sound files with middle stethoscope gain. Lastly, the “HS_PATHOLOGY_no_adjustment_combined_with_LS_NORMAL” set contains various combinations of a heart pathology, heart murmur, sound signal with separated lung sounds from the normal breathing aortic, mitral, pulmonic, and tricuspid chest areas, as well as normal breathing lung sound files with middle stethoscope gain. Details about both the original and pathology heart sounds and lung sounds signals are presented in Appendix A: Description of Input and Reference Heart/Lung Signals. Details about the specific combined signals contained in the assessment signal set, as well as the experts’ analysis are provided in Table XIV.

A questionnaire was provided for the SME to complete for each of the eight signals assessed. The questionnaire is provided in Appendix B: Questionnaire for qualitative

assessment of modified heart sound and lung sound signals. Overall the assessment is favorable. Out of eight signals only one signal, signal A2, is deemed as sounding unrealistic, containing artifacts and having in incorrect timing of pathology. The signal is assessed to have too much bass. The assessments of realism, presence of artifacts and timing of signals A4, A5, and A6 are inconclusive, due to the presence of a low pitched hum. But the SME felt that the separation or “splitting” of the heart sound signal and lung sound signal is correct. Signals A1, A3, and A7 are deemed to sound realistic, lack artifacts, and have correct timing. The assessment is similar for signal A8, however an artifact of a background hum is present in signal A8. The SME did feel that the combination of this signal is correct. For the signals with favorable assessments, there seem to be a common characteristic of a difference in amplitude of the heart sounds and lung sounds, with the lung sounds being too loud or the heart sounds needed to be louder.

TABLE XIV QUALITATIVE ASSESSMENT RESULTS

ID	File Name	Description	Assessment	Comment
A2	Tricuspid_Normal_breathing_WT_HS_adj_Aortic_Normal_breathing_WT_LS.wav	Tricuspid Normal HS / Aortic Normal LS	Unrealistic sound Artifacts present	Too much bass
A4	STG_HeartS_EjectionMurmur_DS_adj_BreathingNormally_WT_LS.wav	STG HeartS Ejection Murmur HS / Breathing Normally LS	Unsure on sound realism and artifact presence. Correct Timing	Low pitched hum obscures heart sound. Sound splitting accurate
A6	STG_HeartS_EjectionMurmur_DS_adj_Mitral_Normal_breathing_WT_LS.wav	STG HeartS Ejection Murmur HS / Mitral Normal LS	Unsure on sound realism and artifact presence. Correct Timing	Low pitched hum obscures heart sound. Sound splitting accurate
A8	Tricuspid_Normal_breathing_WT_HS_adj_STG_LungS_CHF_Crackles.wav	Tricuspid Normal HS / STG LungS CHF Crackles LS	Realistic Sound, Artifacts present Correct Timing	Background hum otherwise good combo.

4.2 Quantitative Results

A quantitative analysis was also performed. The assessment focused on verifying and validating the signal separation, beat detection, combination of different signals, and the final presentation of a realistic signal to a user. The analysis was performed in three phases. Phase I: Quantitative assessment of separation of heart sound and lung sound signals procedure was performed to validate that the WT-ANC filter correctly separates heart and lungs sounds. Phase II: Quantitative assessment of signal modification procedure was performed to validate the signal modification including proving the feasibility of utilizing Scheirer's beat detection algorithm [5] for heartbeat detection and localization and plausibility of modifying a signal with abnormal pathology to produce a realistic heart and lung sound signal. This portion of the model was validated separately from the heart sound and lung sound signal separation, in order to preclude any artifacts of the signal separation from affecting the performance of the algorithms to detect heart rate and heart beat localization, which are the main focus areas of the dissertation. Phase III consisted of validating the complete model by applying all portions of the model to a simulated pair of heart and lung signals.

To best assess the accuracy of the beat detection and localization, signal substitution, and signal re-combination portions of the model, it was determined that simulated signals would best provide a reference signal for input into these sections of the model. Two algorithms of basic heart signals and lung signals were chosen and are described in the following sections, Section 4.2.1 Heart signals and Section 4.2.2 Lung sound signal [39].

4.2.1 Heart Signals

The heart signal generation included simulating the shapes of the electrocardiogram for two different signals that are similar but vary in heart rate. Two signals, typical of a mother and fetus, were simulated. The first signal was simulated by creating an electrocardiogram (ECG) signal that a mother's heart might produce assuming a 4 KHz sampling rate. The heart rate for this signal is approximately 89 beats per minute, and the peak voltage of the signal is 3.5 millivolts. The heart of a fetus beats noticeably faster than that of its mother, with rates ranging from 120 to 160 beats per minute. The amplitude of the fetal electrocardiogram is also much weaker than that of the maternal electrocardiogram. The simulated fetus electrocardiogram signal was created corresponding to a heart rate of 139 beats per minute and a peak voltage of 3.5 millivolts. These signals were originally used for an application of applying adaptive filters to fetal electrocardiography for adaptive noise cancellation, in which a maternal heartbeat signal is adaptively removed from a fetal heartbeat sensor signal [39]. It is known that an ECG is an electrical signal and not a sound signal, however, the rationale for its use is due to 1) the fact that an ECG signal corresponds to the heart beat frequency and heart sound signal in time and 2) the desire to have a “clean” signal for validating the separation, heart rate detection, heartbeat localization and signal modification algorithms. Furthermore, due to the original application of the simulated ECG signals, the signals are very relevant for validating this portion of the model, because in this validation, they represent separated heart sound signals from the WT-ANC filter, and are of sampling rate of 4000 Hz similar to the down sampled rate of 4410 Hz of the WT-ANC filter.

A time domain signal representation and PSD of the 89 bpm heart signal, SimHS0

are shown in Fig. 23. and Fig. 24., respectively. The simulated heart signal plot in Fig. 23. includes a time domain in samples and a signal value range in millivolts. The PSD plot in Fig. 24. shows that most of the power is located below 100 Hz and is minimal after 200 Hz, which is typical of a heart signal.

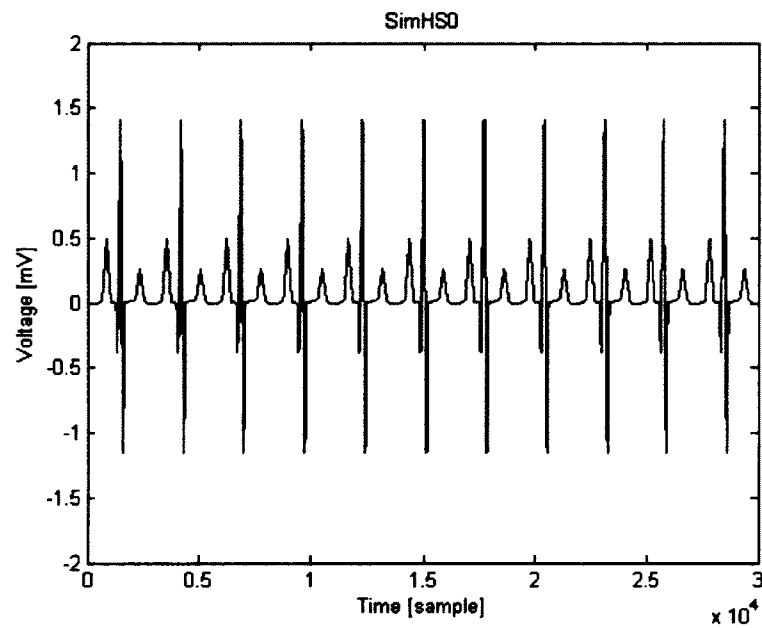


Fig. 23. Simulated heart signal, SimHS0, at 89 bpm.

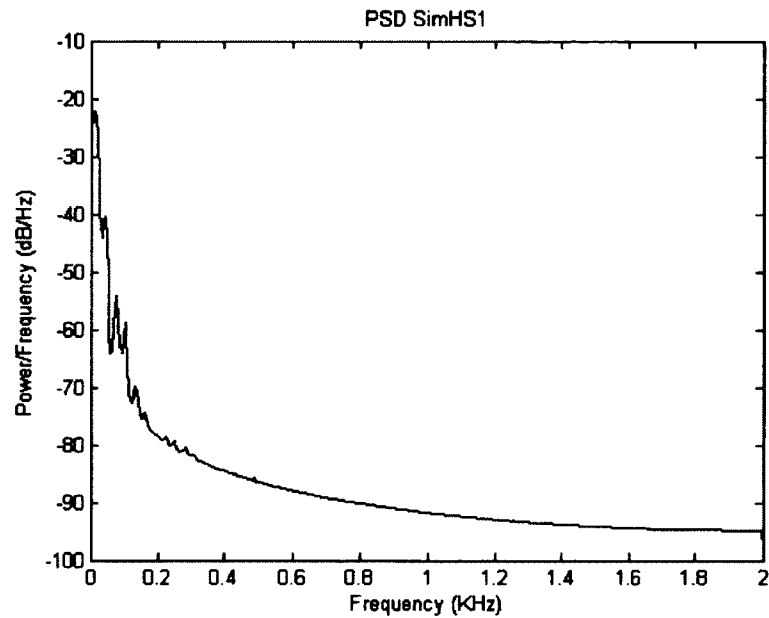


Fig. 24. PSD of simulated heart signal, SimHS0 (89 bpm).

A time domain signal representation and PSD of the 139 bpm heart signal, SimHS1 are shown in Fig.25. and Fig.26., respectively. The simulated heart signal plot in Fig. 25. includes a time domain in samples and a signal value range in millivolts. The PSD plot on Fig. 26. shows that most of the power is located below 100 Hz and is minimal after 200 Hz, which is typical of a heart signal.

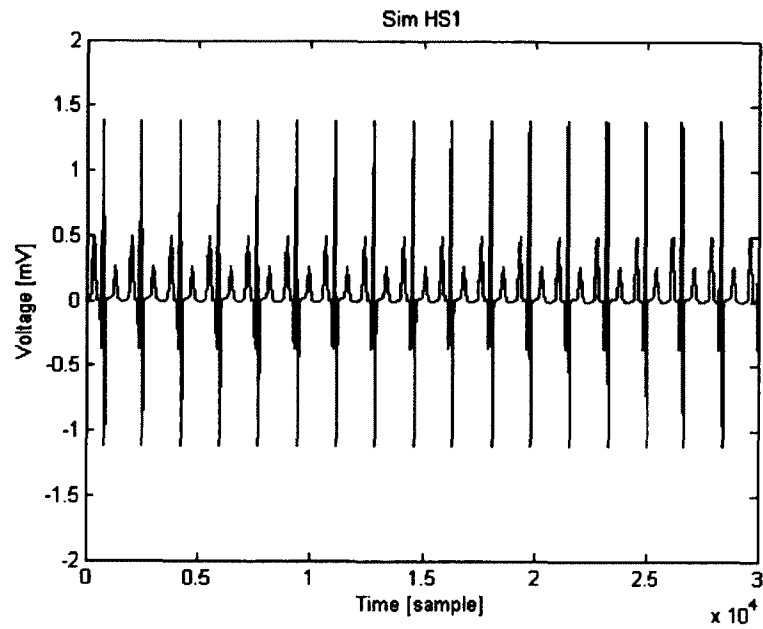


Fig. 25. Simulated heart signal, SimHS1, at 139 bpm.

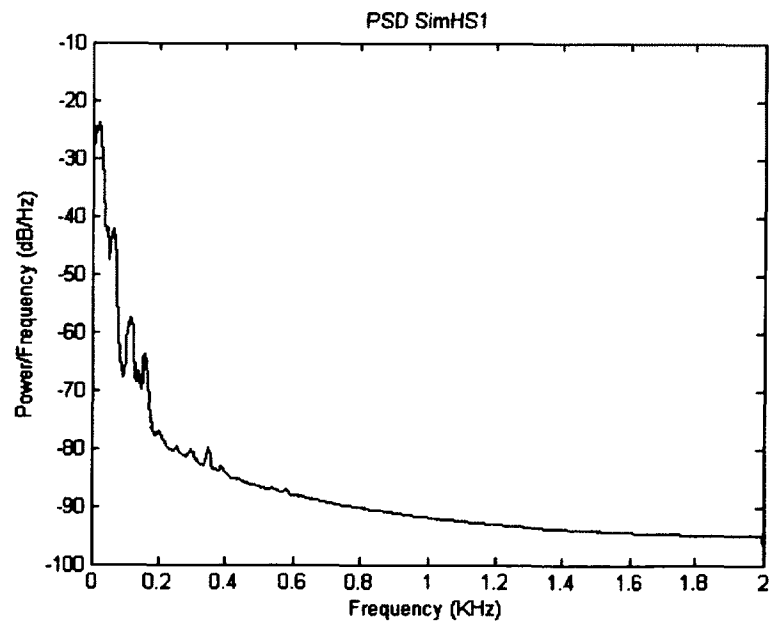


Fig. 26. PSD of simulated heart signal, SimHS1 (139 bpm).

4.2.2 Lung Sound Signal

The simulated lung sound was created by utilizing the Gaussian random number function in MatLab with a domain in samples of 30,000 and a range between ± 0.5 to form a noise signal to represent breath sounds in millivolts. While the random noise signal is not a true representation of a lung sound signal, it is adequate to represent a lung signal which, when combined with a heart signal is perceived as noise, when the heart signal is of interest. While both heart and lung signals are of interest for the validation, and in this study in general, for signal separation and combination, the heart signal is the signal of interest for validating the heartbeat detection and localization. SimLS, sampled at 4 KHz, is 7.5 seconds in duration. The time domain signal representation of the simulated lung signal SimLS, is shown in Fig. 27. It can be seen that the signal has characteristics typical of random noise. The PSD of the lung signal is shown in Fig. 28. The plot contains a frequency domain of 0 – 2,000 Hz and a signal value of power calculated in dB/Hz. The PSD indicates that the power of the signal drops off considerably at the frequency range from 600 – to 2,000 Hz. While this is not typical of a lung sound signal, it was deemed an acceptable signal to be used to validate the heart/lung signal separation and heart rate detection and localization on the resulting separated heart signal. A 0.25-second time domain sample of the simulated lung signal is shown in Fig. 29., which shows a better view of the randomness of the noise in the signal.

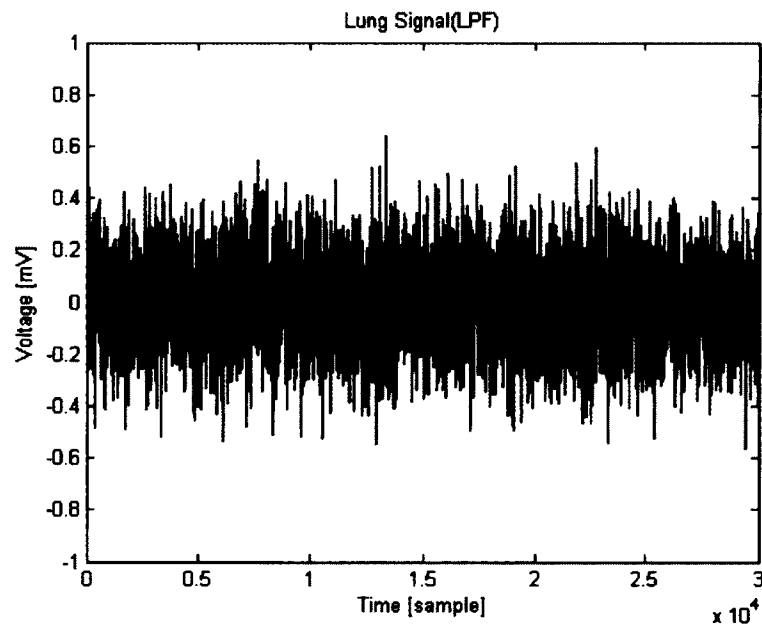


Fig. 27. Simulated lung signal, SimLS, based on random noise.

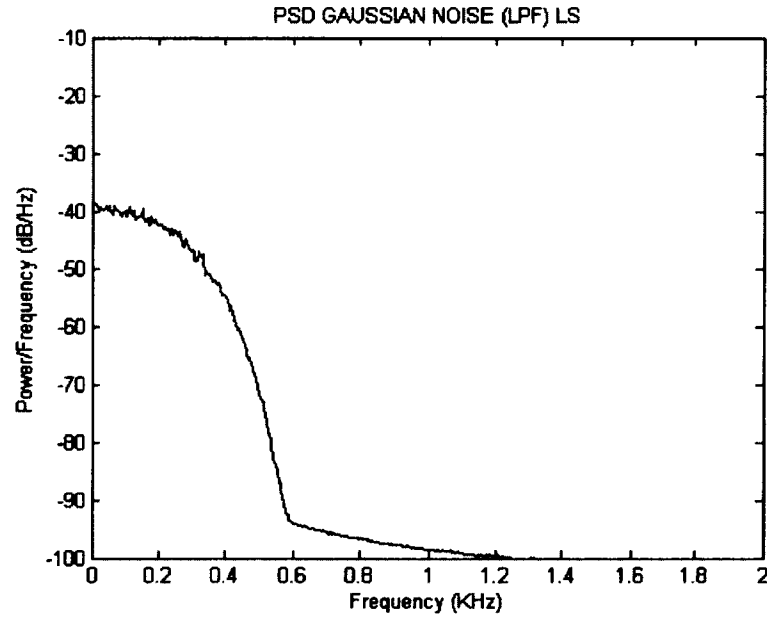


Fig. 28. PSD of the simulated lung signal, SimLS, based on Gaussian random noise.

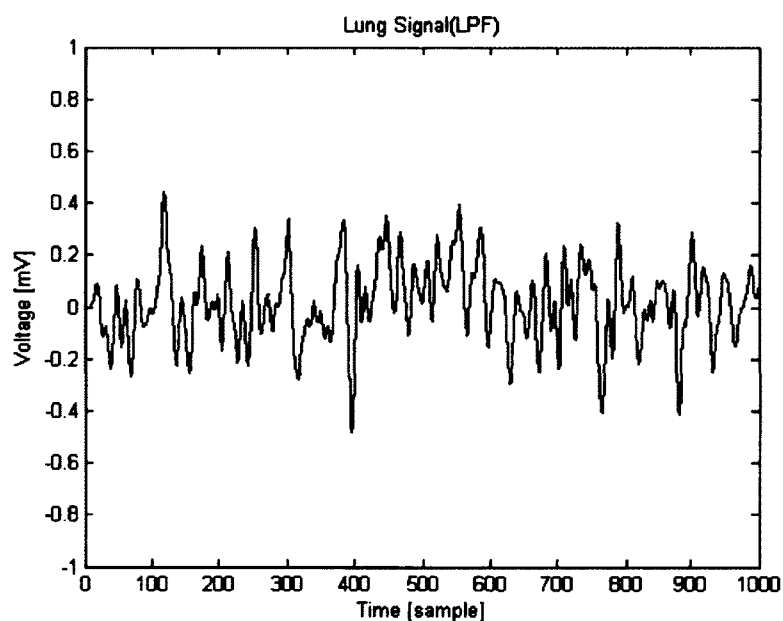


Fig. 29. Simulated lung signal (1/4 Sec).

4.2.3 Methodology

The methodology to perform the quantitative analysis is listed in Table XV Procedure for Phase I: Quantitative Assessment of Separation of Heart Sound and Lung Sound Signals, TABLE XVII Procedure for Phase II: Quantitative assessment of signal modification, and TABLE XIX Procedure for Phase III: Quantitative assessment of the complete model.

TABLE XV
PROCEDURE FOR QUANTITATIVE ASSESSMENT OF PHASE I: SEPARATION
OF HEART SOUND AND LUNG SOUND SIGNALS

Step	Description
2	Combine SimHS1 and SimLS (CombineHS1L)
4	Compare separated HS and LS to SimHS1 and SimLS (Step 1)

The first step of Phase I included creating a simulated heart ECG signal, SimHS1 and a lung signal, SimLS, based on the random noise with amplitude typical of a breath sound signal. The signals, SimHS1 and SimLS, are shown in Fig. 19 and Fig. 21, respectively. The second step of Phase I included combining the simulated heart signal with the simulated lung signal. As previously mentioned, both the heart signal and lung signal were sampled at 4 KHz. The SimHS1 heart signal and the SimLS lung signal were combined through an addition of the signals in the frequency domain. A 7.5-second time domain signal representation and PSD of the combined signal, CombHS1LS, are shown in Fig. 30. and Fig. 31. The plot in Fig. 30., has a time domain in samples and a signal value range in millivolts. When comparing the plot to the heart signal plot in Fig. 23. the addition of the simulated lung signal is clearly evident. The plot in Fig. 31, has a frequency domain from 0 to 2000 Hz samples and a power range calculated in db/Hz. The power is maximum well under 100 Hz, where both the heart signal and lung signal contributes to the power. The spectra tapers off and is “flat” after 200 Hz, where mostly the lung signal contributes to the power.

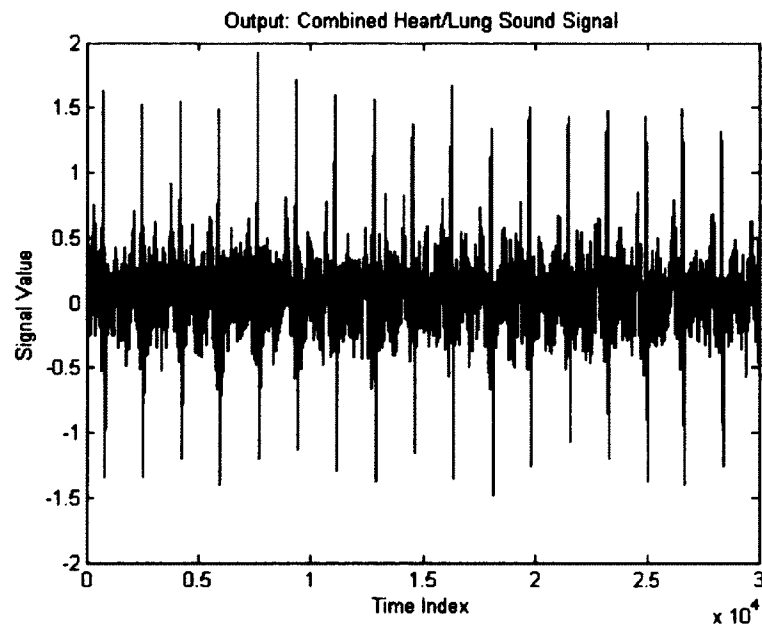


Fig. 30. Combined signal: CombHS1LS (heart signal SimHS1 and lung signal, SimLS).

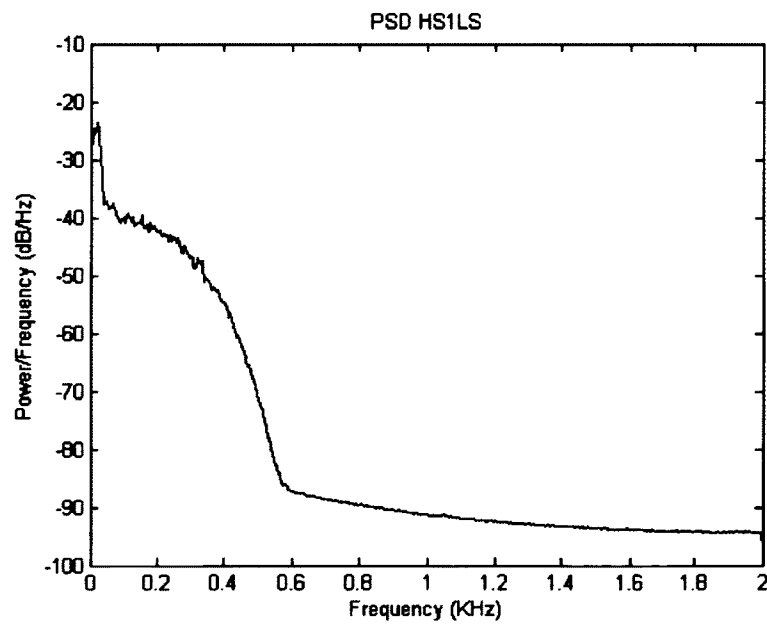


Fig. 31. PSD of the combined signal: CombHS1LS.

The third and fourth steps included applying the WT-ANC filter to the combined heart and lung signal, CombHS1LS, and comparing the resulting separated signals to the original simulated heart ECG signal, SimHS1, and lung signal, SimLS. The results and comparisons are shown in Fig. 32. and Fig. 33. Fig. 32a. and Fig. 32b. show the original and separated heart signals. The plots have time domain in samples and a signal value range in millivolts. When comparing the 28,000 samples or 7 seconds of the separated heart and lung signals, the heartbeats are clearly seen with only minimal noise (lung signal components) in the heart signal, which shows that the WT-ANC did a very good job of separating the signals, from the heart signal perspective. The number of heartbeats differs between the original (Fig. 32a.) and separated (Fig. 32b.) heart signals, due to the fact that the two signals are not representing exact corresponding locations within each signal. The WT-ANC algorithm used a sample set from the middle of the combined heart/lung signal, while the original signal plot is from a location at the beginning of the signal. The PSD in Fig. 32c. and Fig. 32d. have a frequency domain from 0 to 2,000 Hz and power range calculated in dB/Hz. Both PSDs show maximum power below 200 Hz, typical of a heart signal. The PSD of the separated signal matches the trend of the spectra of the original signal. However, the maximum power, well below 100 Hz, of the separated signal is comparable to the original heart signal. However the power levels for frequencies above 100 Hz are higher than the power levels for the same frequencies of the original heart signal, which is most likely due to the minimal presence of lung signal components, which are typically present at frequencies up to 1,500 Hz. The original and separated lung signal plots, shown in Fig. 33a. and Fig. 33b., contain time domain in samples and a signal value range in millivolts. It can be seen that the separated lung

signal in Fig. 33b. closely resembles the original signal in Fig. 33a., and is lacking the presence of heart signal components. The PSD plots in Fig. 33c. and Fig. 33d. have a frequency domain from 0 to 2,000 Hz and a power range calculated in dB/Hz. The PSD of the separated lung signal closely matches that of the original signal, but is consistently at slightly lower level than the original lung signal, most likely due to the absence of some lung signal components, which are included in the heart signal.

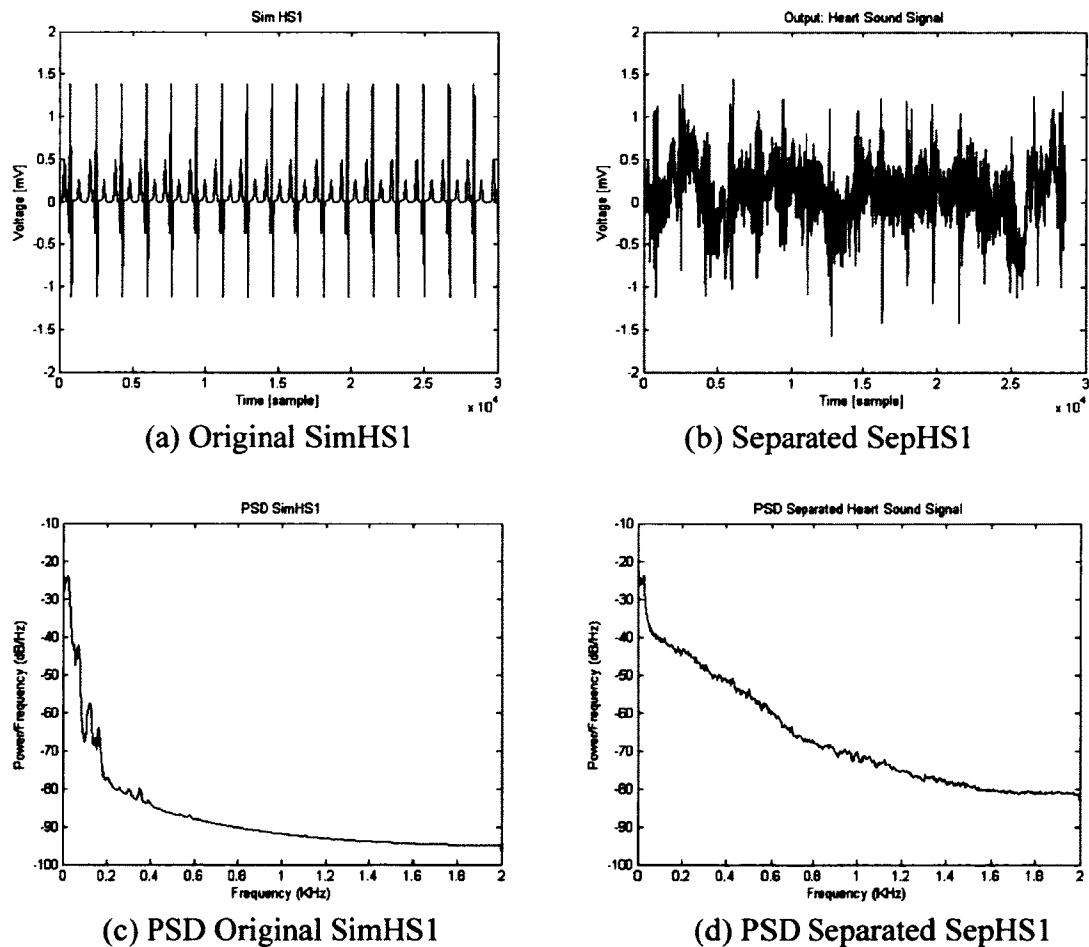


Fig. 32. Comparison of separated heart signal SepHS1 from CombHS1LS.

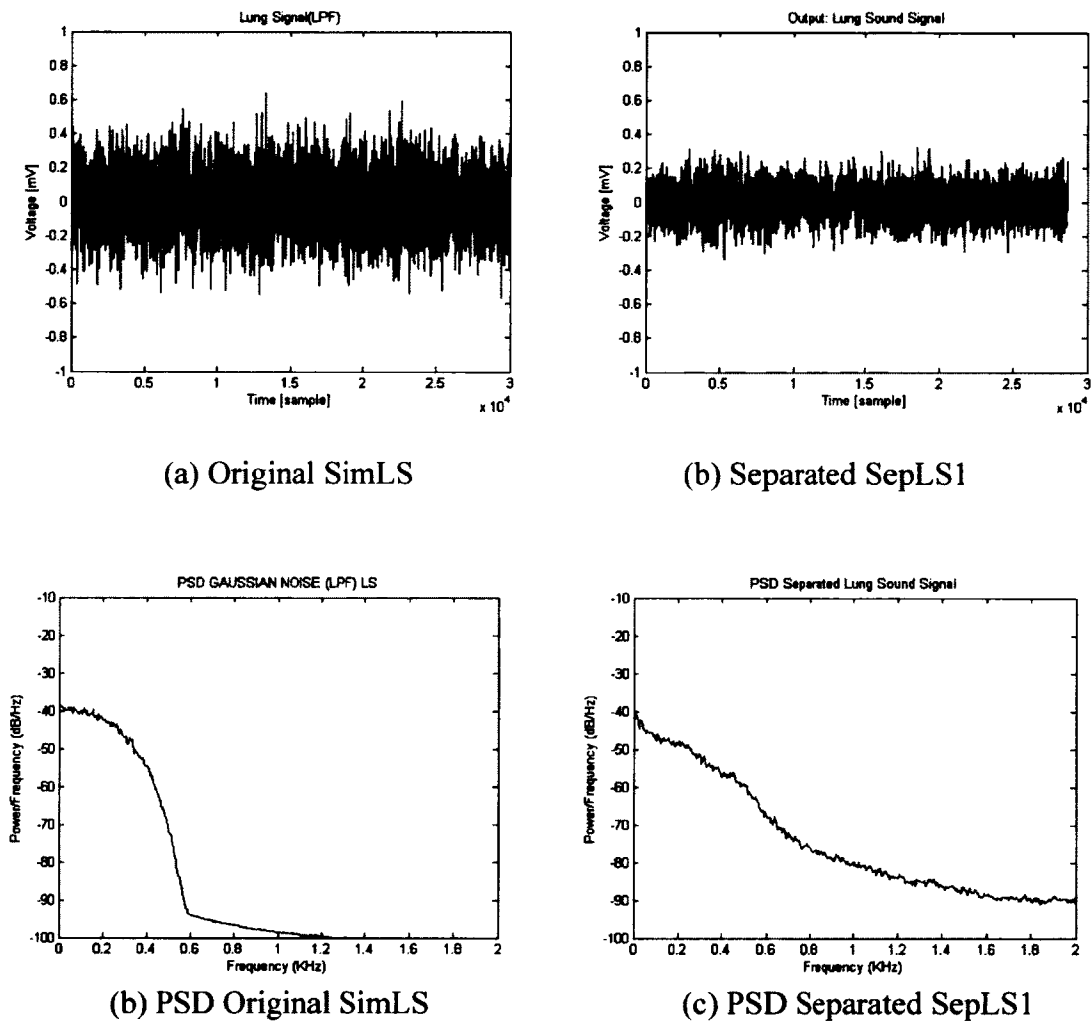


Fig. 33. Comparison of separated lung signal SepLS1 from CombHS1LS.

After the signals were separated, the heartbeat detection and localization algorithm was applied to the separated heart signal. The results are shown Table XVI. The heart rate was detected at 138.97 bpm, which accurately corresponds to the known heart rate of 139

bpm of the original simulated signal, SimHS1. The location of the first beat was identified at sample 1,022. From visual inspection of the CombHS1LS signal in Fig. 30., the identified location of the first heart beat looks to be accurate, as it lies within the range of samples that make up the peak voltage in this particular heart beat.

TABLE XVI
SIMULATED HEART SIGNALS

Signal	Heart Rate (bpm)	First Beat
Original HS1	139	- 1,000

Next, Phase II: Signal modification was validated. This also included validating the heartbeat detection and localization algorithm. The procedure is summarized in Table XVII.

TABLE XVII
PROCEDURE FOR QUANTITATIVE ASSESSMENT OF PHASE II: SIGNAL
MODIFICATION

Step	Description
2	Verify Heart Signals
4	Combine SimHS0 with SimLS to use as reference
6	Compare HSLs combinations (from Step 4 and Step 5)

The first step included simulating the two heart ECG signals and one lung signal exactly

like in Phase I Step One, described in Section 5.2.2 Heart sound signals and Section 5.2.3 Lung sound signal. The first simulated ECG signal, SimHS0, sampled at 4 KHz, is 7.5-seconds in duration, and is characterized by a heart rate of 89 bpm. A time domain signal representation and the PSD of the heart signal are previously shown in Fig. 23. and Fig. 24., respectively. The second simulated heart signal, SimHS1, sampled at 4000 Hz, is also 7.5-seconds in duration, and is characterized by a heart rate of 139 bpm. A time domain signal representation and the PSD of the heart signal, SimHS1 are previously shown in Fig. 25. and Fig. 26., respectively. SimLS, sampled at 4 KHz, is 7.5 seconds in duration, and is characterized by random noise function with amplitude typical of a breath sound. The PSD and time domain signal representations of the simulated lung signal SimLS, are previously shown in Fig. 27., Fig. 28., and Fig. 29. The second step included a verification of the signals. The beat detection and localization, as presented in Section 3.4 Heartbeat detection and localization, was applied to each heart signal to verify the heart rate and location of the first heartbeat. The results are shown in TABLE XVIII. The calculated heart rate and first beat location for both SimHS0 and SimHS1 by the heart beat detection and localization algorithm match the intended rates of the functions used to generate the signals. A visual inspection was performed on SimLS, which shows that the signal was created correctly per the function used to generate the signal. The third step of the procedure adjusted the SimHS1 signal to closely match the reference signal SimHS0 in heart rate and location of the first heartbeat.

TABLE XVIII
RESULTS FOR HEARTBEAT DETECTION AND LOCALIZATION OF
SIMIULATED HEART SIGNALS

Signal	Heart Rate (bpm)	First Beat Location (Sample #)
SimHS1	138.97	999

Fig. 34. shows the time domain representation of the adjusted simulated heart sound signal, SimHS1, based on SimHS0 as the reference. Fig. 35. shows the computed power spectral density of adjusted signal, SimHS1. Fig. 36. includes a comparison of the simulated heart sound signals: SimHS0 (reference) vs. SimHS1 (adjusted) vs. SimHS1 (original). From a visual inspection, it can be seen that the heart rate SimHS1 has been adjusted to match that of SimHS0. The detected heart rate was calculated at 91.43 bpm, which is shown in Table XII. From a visual inspection, it can be seen that the location of the adjusted SimHS1, SimHS1adj, is not an exact match to the location of the first heartbeat of the reference signal SimHS0. It is thought that this difference is acceptable due to the fact that the signals are different in their structure, but more importantly, the adjusted HS1 signal, SimHS1adj as a whole does align closely with the reference signal SimHS0. It is thought that the signals would be more of a continuous nature and the initial location is not as important as matching the heart rate, which will be pertinent throughout the entire signal presentation to the medical student.

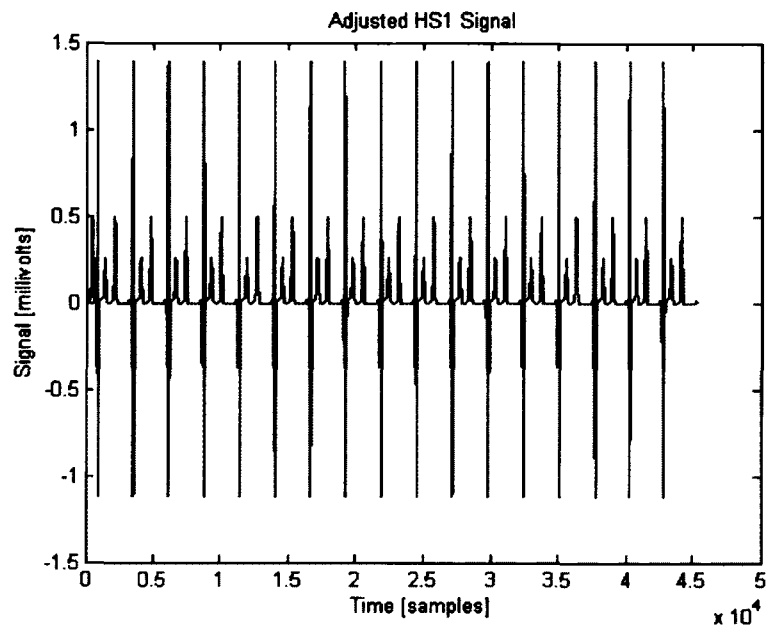


Fig. 34. Adjusted simulated heart signal, SimHS1adj, based on SimHS0 as reference.

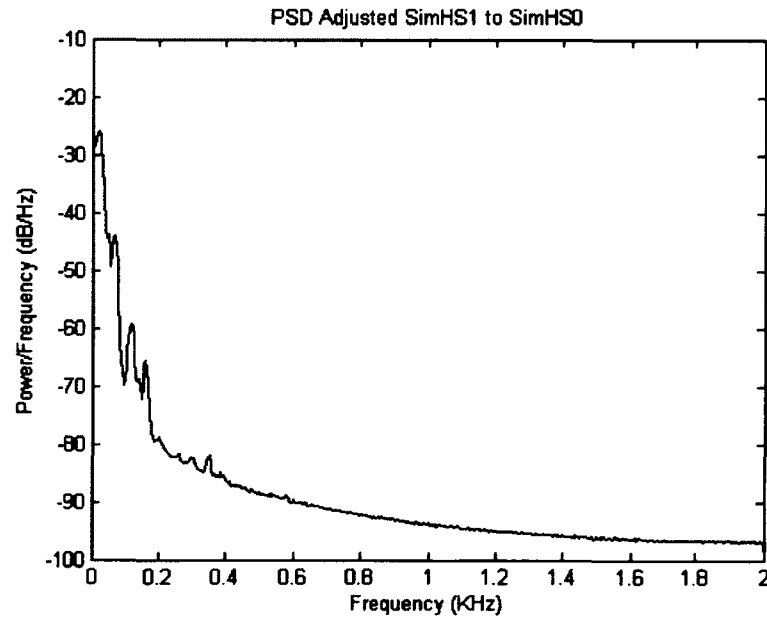


Fig. 35. PSD of adjusted simulated heart signal, SimHS1adj, based on SimHS0 as reference.

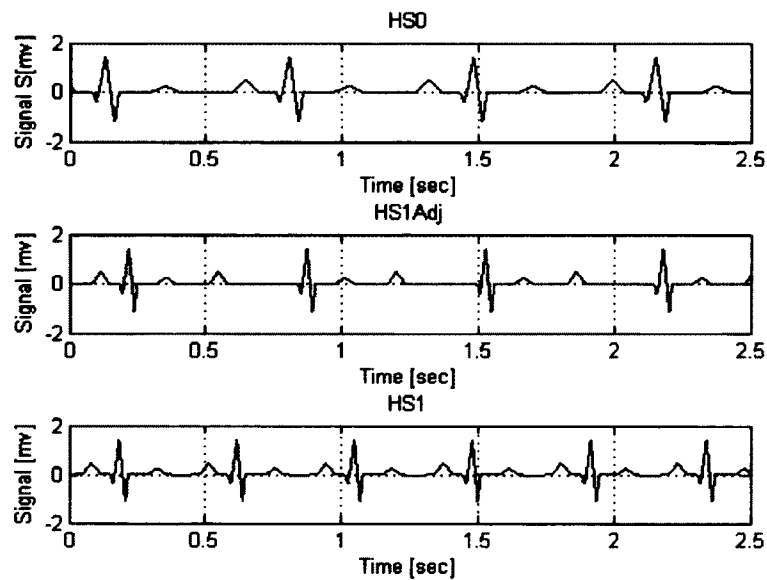
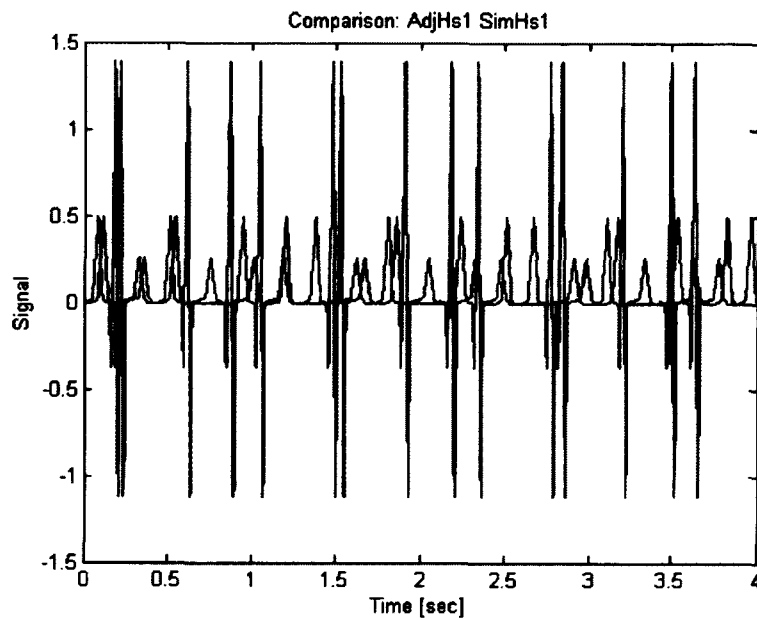


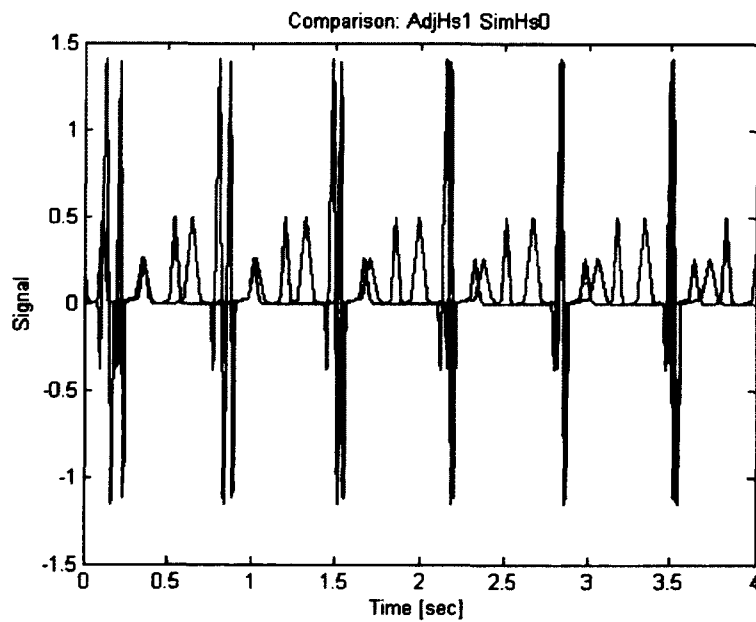
Fig. 36. Simulated heart sound signals: SimHS0 (reference) vs. SimHS1adj (adjusted) vs. SimHS1 (original).

A comparison of the time domain representations of original and adjusted simulated heart sound signal SimHS1 is shown in Fig. 37. It can be seen that the signal has been shifted and that the rate of heartbeats has decreased. The figures show only a small window of the signal was used for the validation. In practice the signal would be much longer and the adjustment would be performed in a more continuous fashion for the entire length of the signal. A comparison of the time domain representations of the simulated heart sound signals, SimHS0 (reference) and SimHS1adj (adjusted) is shown in Fig. 38. This comparison shows that the adjusted signal is not a perfect match in locations of the heartbeats. But, as previously mentioned, the heart rates are a very close match, which is deemed a major requirement for modifying a signal, such a pathology signal, to match a reference signal for a continuous real-time application.



Blue: Sim HS1 (Source), Green: Sim HS1 (ADJUSTED)

Fig. 37. Simulated heart signal comparison:
SimHS1 (source) vs. SimHS1adj (adjusted).



Blue: SimHS0 (Reference), Green SimHS1 (Adjusted)

Fig. 38. Simulated heart signal comparison:
SimHS0 (reference) vs. SimHS1adj (adjusted).

Step Four of the validation included combining the reference signals SimHS0 and SimLS to use as a reference for comparing the combination of the adjusted SimHS1 heart signal, SimHS1adj, with the lung signal, SimLS. For each pair, the signals were combined through an addition of the signals in the frequency domain. The time domain representation and PSD of the reference signal, SimHS0SimLS, are previously shown in Fig. 30. and Fig. 31., respectively. Step Five of this phase of the quantitative validation combined the adjusted simulated heart signal, SimHS1adj, with the simulated reference lung signal, SimLS, through a frequency domain addition. The time domain representation and PSD of the resulting combined signal are shown in Fig. 39. and Fig. 40., respectively. The 7.5 second plot in Fig. 39., has a time domain in samples and a signal value range in millivolts. The plot shows the lung signal combined with the heart signal. The PSD plot in Fig. 40., has a frequency domain from 0 to 2,000 Hz samples and a power range calculated in db/Hz. The power spectra also match the power spectra of the reference signal combination, SimHS0SimLS, as shown in Fig. 29. The power is maximum for the frequency range below 200 Hz, where the heart signal values are combined with the lung signal. The spectra tapers down and is consistently “flat” after 200 Hz, where mostly the lung signal contributes to the spectra.

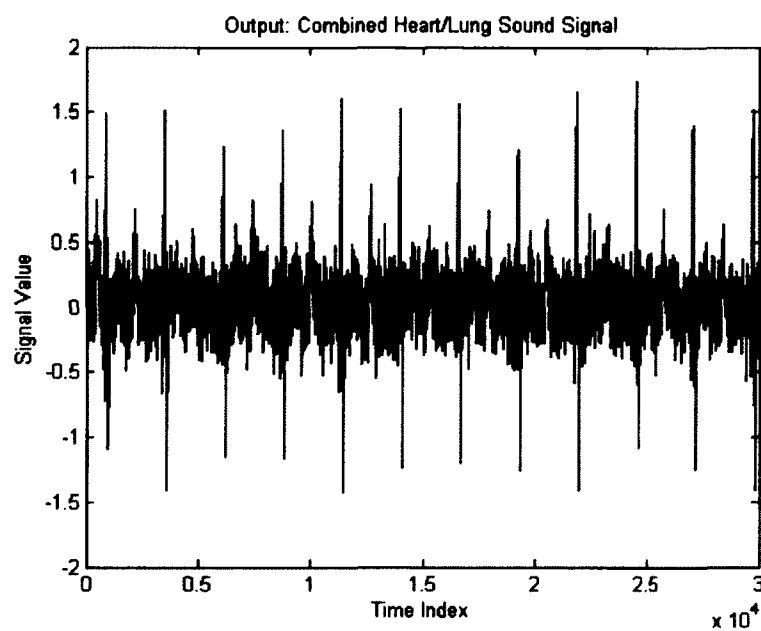


Fig. 39. Combined signal: adjusted simulated heart signal SimHS1adj and simulated lung signal SimLS.

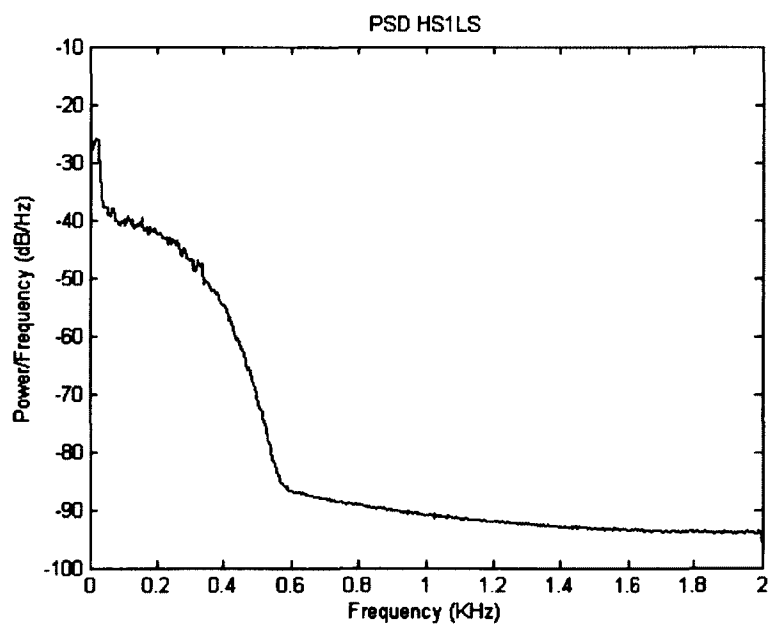
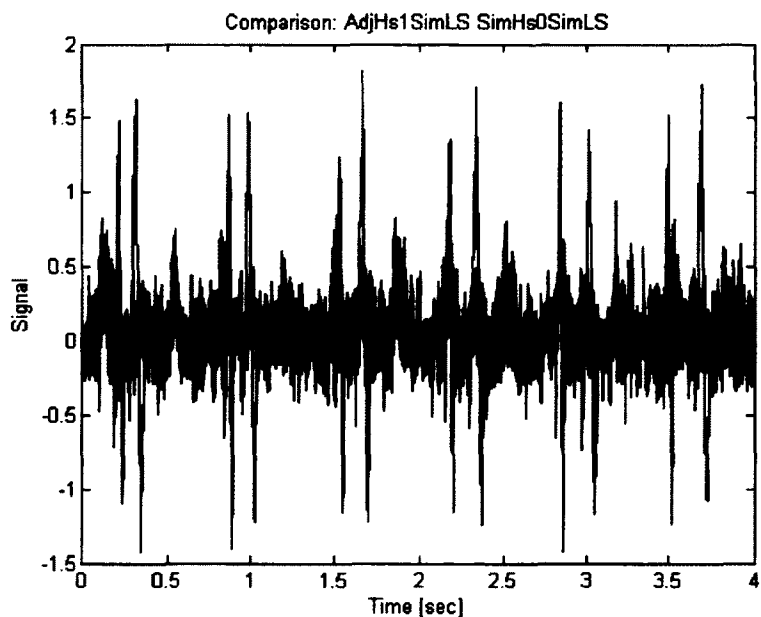


Fig. 40. PSD of combined signal: adjusted simulated heart signal simHS1 and simulated lung signal SimLS.

The final step in this validation phase included a comparison of the reference HSLS combination, SimHS0SimLS with the adjusted heart signal and reference lung signal, SimHS1adjSimLS. The comparison is shown in Fig. 41., which has a time domain in seconds and a signal value range in millivolts. Visually, it can be seen that the amplitude and shape of the signals are comparable, and that the beat locations of the adjusted signal combination do not perfectly align with the beat locations of the reference combination. However, the adjusted signal combination does closely resemble the reference combination in heart rate. The reference signal HS0 possessed a heart rate of 89 bpm. The beat detection algorithm detected a heart rate of 89.12 bpm. The original HS1 signal possessed a rate of 139 bpm and the beat detection algorithm detected a heart rate of 138.97 bpm. The HS1 signal was adjusted and the beat detection algorithm detected an adjusted heart rate of 90.74 bpm.



Green: Combined SimHS0 SimLS (Reference), Blue Combined SimHS1 Adjusted SimLS

Fig. 41. Comparison of combined signals: (reference) simulated heart signal SimHS0 and simulated lung signal SimLS vs. adjusted simulated heart signal SimHS1adj and simulated lung signal SimLS.

The final phase, Phase III, of the quantitative validation involved completing an assessment of the complete model. A summary of the procedure is presented in Table XIX.

TABLE XIX
PROCEDURE FOR QUANTITATIVE ASSESSMENT OF PHASE III: COMPLETE MODEL

Step	Description
2	Combine SimHS0 and SimLS (CombHS0LS)
4	Adjust (bpm and first beat location) SimHS1 to SepHS0 (SimHS1adj)
6	Compare HSLs combinations (from Step 3, Step 7 and Step 8)

The first step of the quantitative validation of the model involved creating the two simulated heart signals and lung signal as described in Phase I: Quantitative assessment of signal separation, of this section. The second step combined the simulated heart signal, SimHS0, with the simulated reference lung signal, SimLS, through a frequency domain addition. The time domain representation and PSD of the resulting combined signal are shown in Fig. 42. and Fig. 43., respectively. The plot in Fig. 42., has a 7.5-second time domain in samples and a signal value range in millivolts. The plot clearly shows the successful addition of the lung signal throughout the heart signal, as compared to the original lung signal, SimLS (Fig. 29.), and heart signal, SimHS1 (Fig. 25.). The plot in Fig. 43., has a frequency domain from 0 to 2,000 Hz samples and a power range calculated in db/Hz. The power is maximum in the frequency range under 200 Hz, where the heart signal values are combined with the lung signal. The spectra tapers off and is consistently “flat” after 200 Hz, where mostly the lung signal contributes to the spectra.

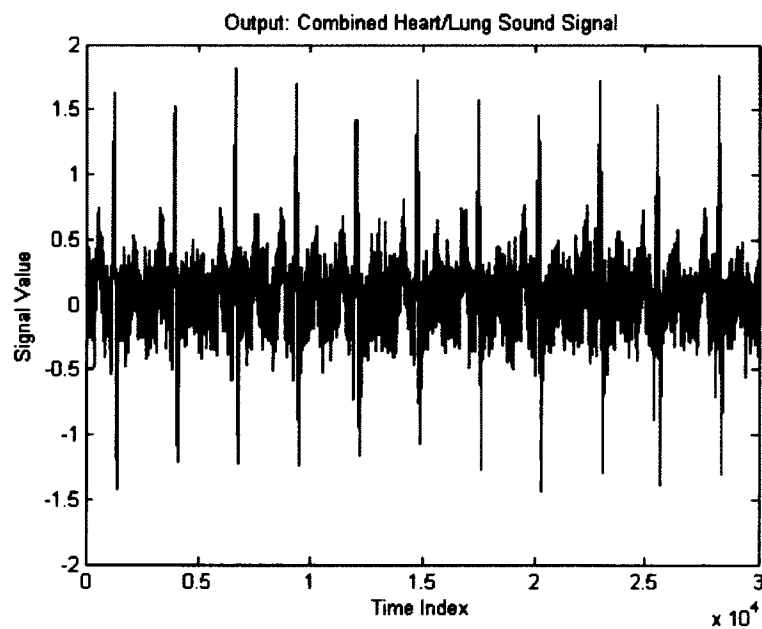


Fig. 42. Combined simulated heart signal SimHS0 and simulated lung signal SimLS (CombHS0LS).

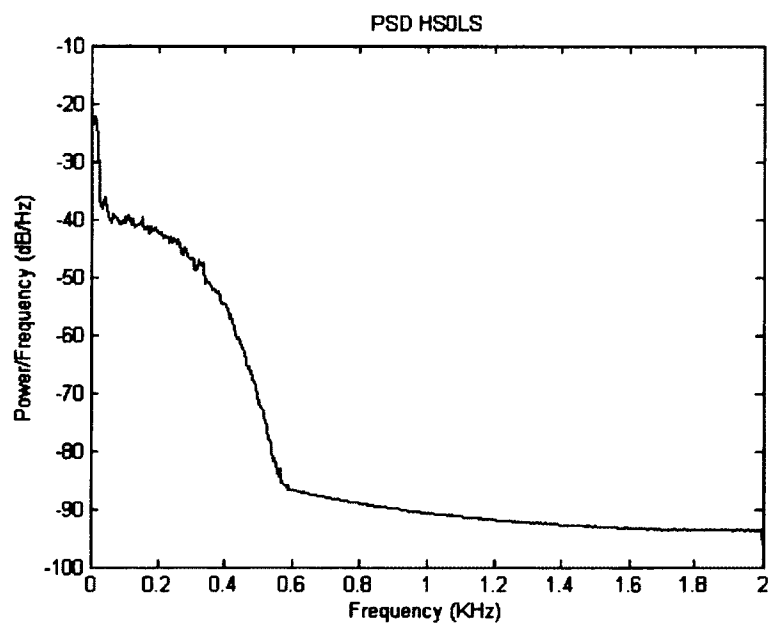


Fig. 43. PSD of Combined simulated heart signal SimHS0 and simulated lung signal SimLS (CombHS0LS).

The third step in the procedure applied the WT-ANC filter to the combined heart/lung signal, CombSimHS0SimLS, to separate the heart signal and lung signal, as specified in Phase I: Quantitative assessment of separation of heart sound and lung sound signals, of this section. The time domain representation and PSD of the resulting separated heart signal (SepHS0) and lung signal (SepLS0) are shown in Figs. 44. - 47., respectively. The separated heart signal plot in Fig. 44. includes a 4.5-second time domain in samples and a signal value range in millivolts. The separated heart signal plot indicates 10.5 heartbeats in the 7 second time period, which matches a heart rate of 89 bpm. The amplitude matches that of the original heart signal with a range of ± 3.5 millivolts. The PSD plot on Fig. 45. shows that most of the power is located below 100 Hz and is minimal after 200 Hz, which is typical of a heart signal. The plot in Fig. 46., has a 7-second time domain in samples and a signal value range in millivolts. The shape of the signal resembles the original lung signal as shown in Fig. 27. The peaks above 0.5 millivolts and below -0.5 millivolts are contributed by heart sound components that are included in the signal. The plot in Fig. 47. has a frequency domain from 0 to 2,000 Hz samples and a power range calculated in db/Hz. The power is maximum for frequencies less than 200 Hz. The spectra tapers off and is consistently “flat” after 200 Hz, where mostly the lung signal contributes to the spectra.

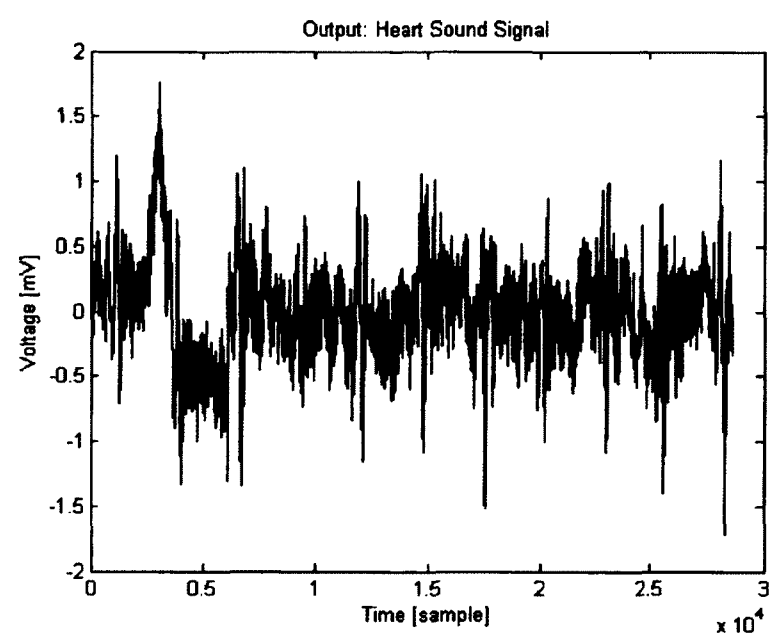


Fig. 44. Separated heart signal, SepHS0.

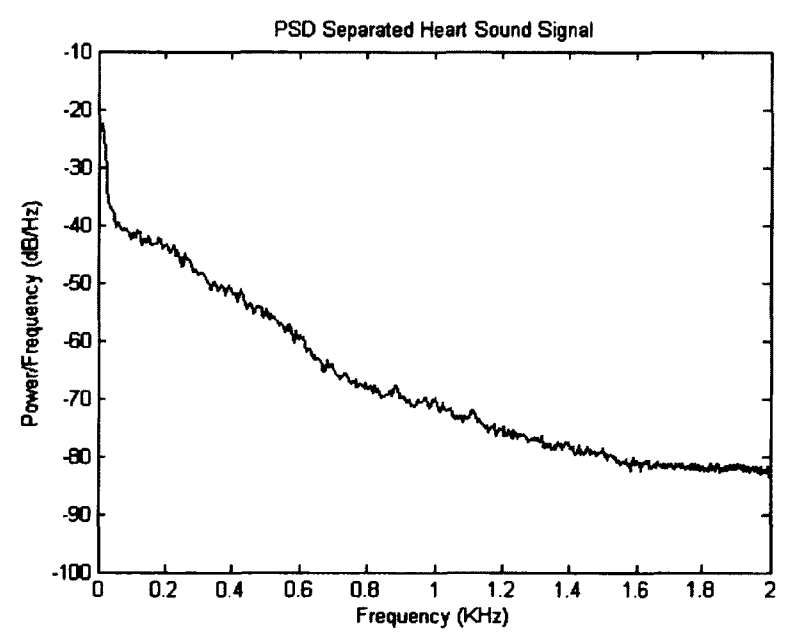


Fig. 45. PSD of Separated heart signal, SepHS0.

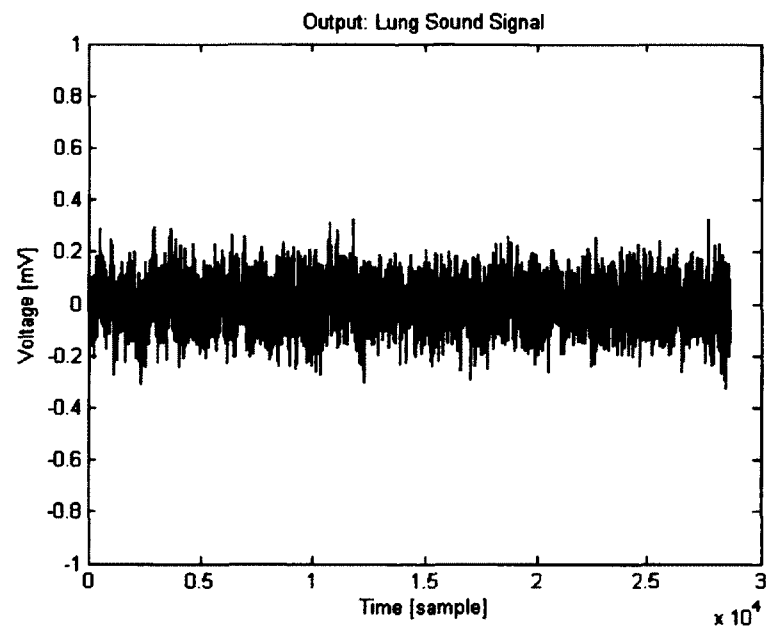


Fig. 46. Separated lung signal, SepLS0.

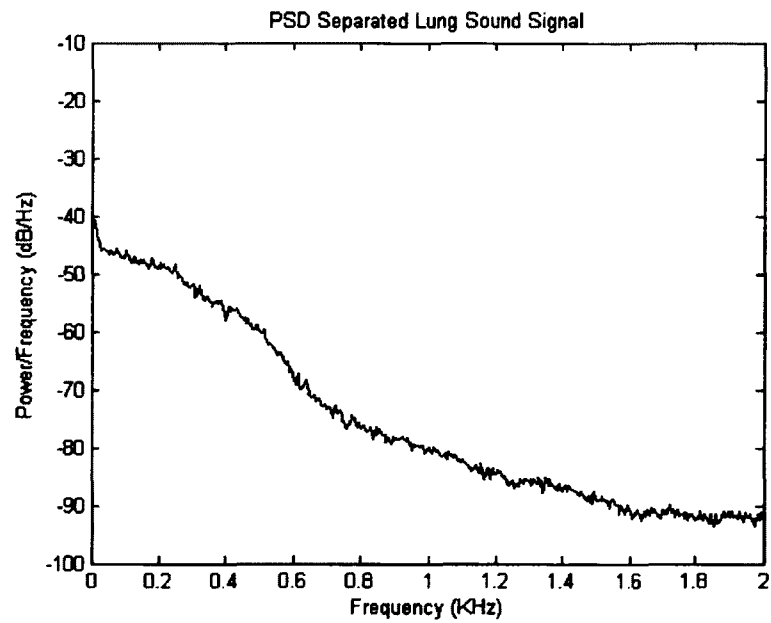


Fig. 47. PSD of separated lung signal, SepLS0.

The fourth step of the procedure adjusted the separated HS1 based on the separated heart signal, SepHS0 as a reference, as presented in Phase II: Quantitative assessment of signal modification, of this section. The time domain representation and PSD of the adjusted HS1 heart signal (SimHS1adj) are shown in Fig. 48. and Fig. 49., respectively.

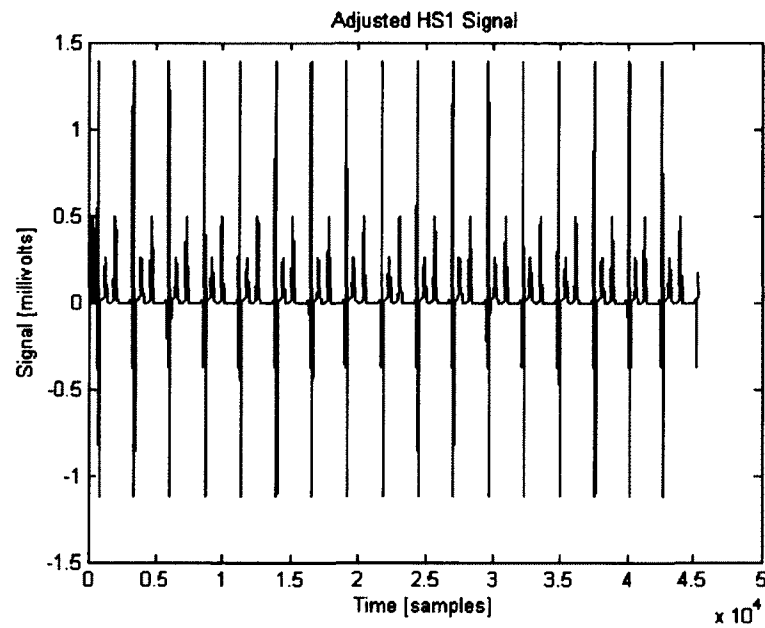


Fig. 48. Adjusted heart signal, SimHS1adj, based on separated HS0, SepHS0.

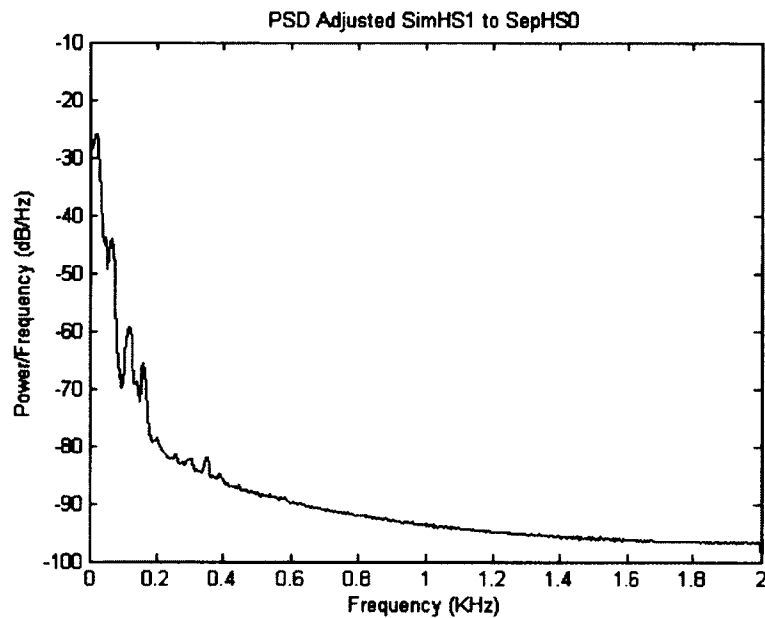


Fig. 49. PSD of adjusted heart signal, SimHS1adj.

Fig. 50. includes a comparison of the simulated heart sound signals: SepHS0 (reference) vs. SimHS1 (adjusted) vs. SimHS1 (original). From a visual inspection, it can be seen that the heart rate SimHS1 has been adjusted to match that of SepHS0. The detected heart rate was calculated at 91.43 bpm, which is shown in Table XII. From a visual inspection, it can be seen that the location of the adjusted SimHS1, SimHS1adj, is not an exact match to the location of the first heartbeat of the reference signal SepHS0. It is thought that this difference is acceptable due to the fact that the signals are different in their structure, but more importantly, the adjusted HS1 signal, SimHS1adj as a whole does align closely with the reference signal SimHS0, but should be adequate for presenting a realistic modified signal to the medical student.

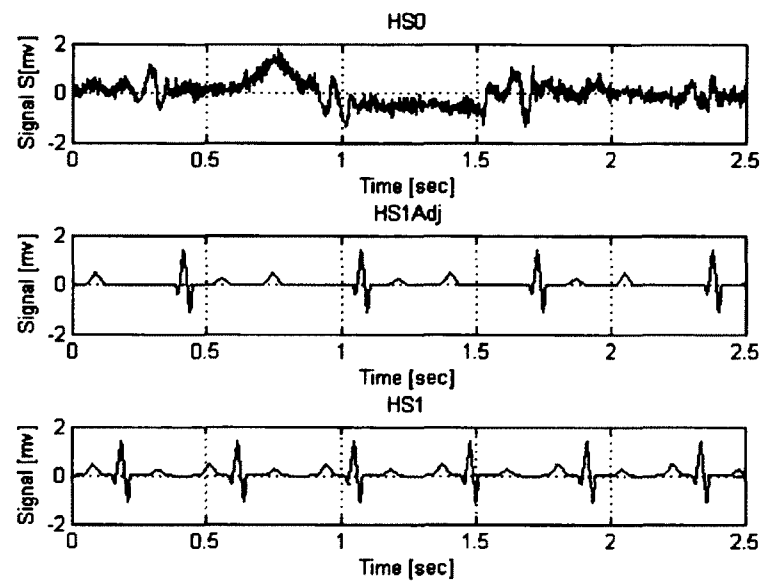


Fig. 50. Simulated heart sound signals: SepHS0 (reference) vs. SimHS1adj (adjusted) vs. SimHS1 (original).

The fifth step of the procedure combined the adjusted heart signal, SimHS1adj, with the reference separated lung signal, SepLS0. The time domain representation and PSD of the resulting combined signal are shown in Fig. 51. and Fig. 52., respectively. The plot in Fig. 51., has a 7-second time domain in samples and a signal value range in millivolts. The plot shows the lung signal combined with the heart signal. The signal resembles the adjusted heart signal AdjSimHs1 and separated lung signal SepLS0, as shown in Fig. 48 and Fig. 46, respectively. The plot in Fig. 51., has a frequency domain from 0 to 2,000 Hz samples and a power range calculated in db/Hz. The power is maximum under 200 Hz, where the heart signal values are combined with the lung signals. The spectra tapers off and is consistently “flat” after 200 Hz, where mostly the lung signal contributes to the spectra. Fig. 53. presents a comparison of the simulated combined heart/lung signals:

CombSimHS0SimLS (reference) and CombSimHS1SimLS (reference) vs. CombSepHS1adjSepLS (result). The plot in Fig. 53., has a 4 second time domain and a signal value range in millivolts. From a visual inspection, it can be seen that the beat locations of the adjusted signal combination do not perfectly align with the beat locations of the reference combination. However, the adjusted signal combination does closely resemble the reference combination in heart rate.

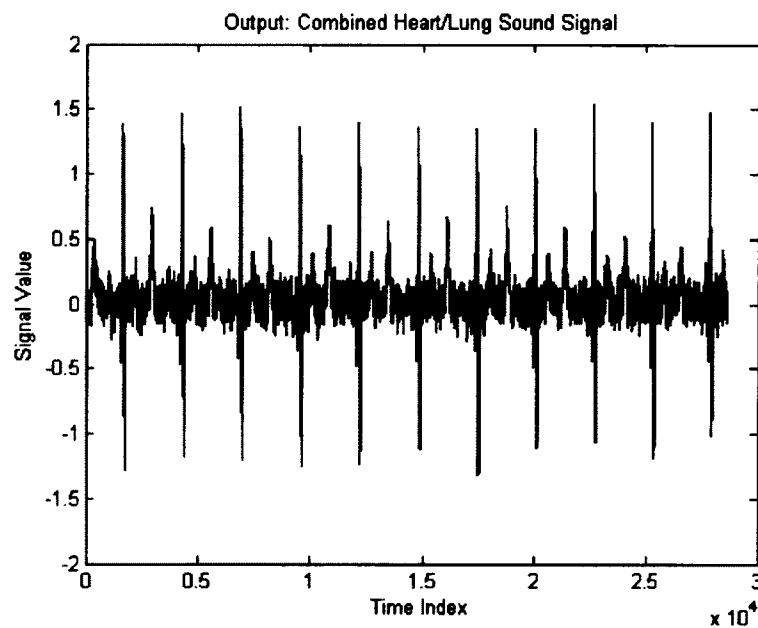


Fig. 51. Combined signal: adjusted separated heart signal SepHS1adj and separated lung signal SepLS1 (CombSepHS1adjSepLS1).

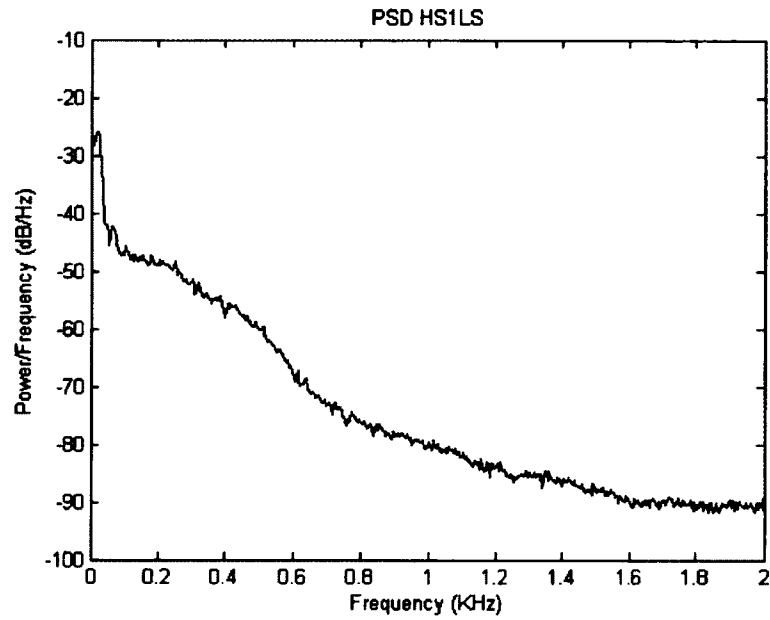


Fig. 52. PSD of combined signal, CombSepHS1adjSepLS1.

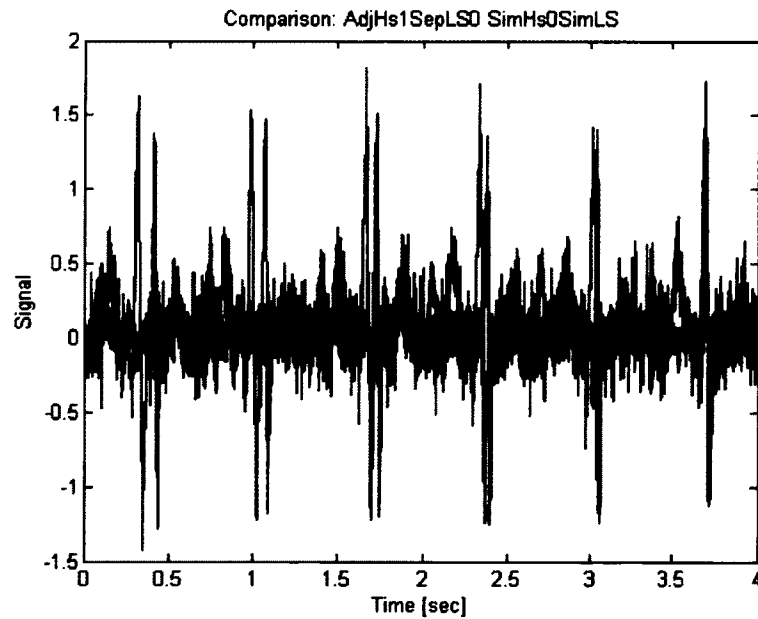


Fig. 53. Comparison of combined signals: (reference CombHS0LS) simulated heart signal SimHS0 and simulated lung sound signal SimLS vs. (CombSimHS1adjSepLS0) adjusted heart signal SimHS1adj and separated lung signal SepLS0.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

This chapter discusses the conclusions and recommendations of the dissertation. The discussion of the conclusions will present a review and summary of the dissertation research, identification of the main methods used, and a discussion of their implications in the study.

5.1 Problem Statement and Methodology

- 1) To improve the presentation of an augmented SP with various abnormalities in a real-time and realistic setting to the practicing doctor, there is an identified need to automate a system to combine simulated heart and lung pathology with real SP breath and heart sounds. The research referenced in this dissertation focused on developing plausible signal modification methods and algorithms, which may be utilized with, or within, a modified electronic stethoscope. Research was conducted on applying methods from tempo and beat analysis of acoustic musical signals to heart signal analysis to detect the heart rate and heartbeat locations in an efficient manner applicable to a real-time heart and lung sound signal modification. The two main objectives of the research were to determine an optimum technique of separating heart sounds from lung sounds, to

support real-time pathology signal analysis and modification from two of the techniques reviewed by Gnitecki and Moussavi [4], including the RLS-ANC and the WTC-ANC algorithm developed by Hadjileontiadis and Panas [11], and

- 2) To investigate and prove the plausibility of applying the acoustic music signal tempo and beat detection algorithms of Scheirer [5] to heart rate detection and heartbeat localization.

These techniques are needed to ensure adequate capability to modify real heart sounds and lung sounds in real-time to mimic abnormal pathology, which is the planned application of this developed technology.

The first stage of the model, after processing the input signal, is the heart and lung sound separation. In this case, the heart sound signal is the signal of interest, not the lung sound, as presented in most of the reviewed papers on heart and lung sound analysis.

The first type of ANC that was implemented was the RLS-ANC developed by Gnitecki, Pasterkamp, and Moussavi [6]. The RLS filter was used for the separation of the heart sound signal from the lung sound signal. The second type of adaptive noise cancellation filter that was implemented was the WT-ANC filter as developed by Hadjileontiadis and Panas [11]. The WTC-ANC is a wavelet transform based filter that separates stationary and non-stationary signals. The filtering scheme combines the efficiency of multi-resolution analysis with hard thresholding and has been proven successful in heart sound noise reduction of lung sounds, without requiring any reference signal. With both types of filters, the heart sound signal was separated and, preserved and available for use in the heart sound signal analysis and modification stages of the model.

As mentioned, a main objective of the research was to investigate applying the acoustic music signal tempo and beat detection algorithms of Scheirer [5] to heart signal analysis. The application of the algorithm was used to characterize separated heart sound signals (input) and reference pathology signals in order to modify the reference signal to better match the input signal in terms of heartbeat rate and location of the heartbeats. In addition, the algorithm was also used to verify the heartbeat rate of the adjusted signal. Scheirer's algorithm [5] was implemented in MatLab, with only minor changes.

5.2 Summary of Results

The WTC-ANC filtering method was selected to separate the heart sound and lung sound signals for two reasons. The predominant reason is that the WT filtered HS signals were better suited as input to the heartbeat detection and localization algorithm. This is most likely due to the fact that more of the HS signal is preserved by the WT technique. The RLS technique seems better suited for reducing HS (noise) from the LS signal without the need to preserve the HS signal. Secondly, the WTC-ANC, which does not need a reference signal, is more efficient than that of the RLS-ANC method which generates the reference signal based on the input signal.

A sensitivity analysis was performed on the WTC-ANC algorithm. The analysis shows that the WTC_ANC algorithm has high sensitivity to the various parameters used to configure the filter. Since the results for some of the parameters is different than the parameters as presented by Hadjileontiadis and Panas [11] and Gnitecki, Hossain, Pasterkamp, and Moussavi [12], it is shown that the configuration dependent on characteristic of the input signals. Therefore, specific analysis must be given to configuration parameters based on the characteristics of the input signals.

A separate quantitative analysis was performed on the WT-ANC technique to ensure that it provided acceptable separation of the heart sound signal and lung sound signal. The analysis used combinations of simulated signals as input into the signal separation algorithm and then compared the separated signals to the original input signals. The results were favorable in that, the separated heart signal and lung signal and their associated PSD resembled the time domain representation and power spectra of original signals. In addition, the separated heart signal possessed a heart rate comparable to the known heart rate of the original simulated signal. The identified location of the first beat also corresponded to a beat in the original signal.

Since the main focus of the research was on exploring the feasibility of utilizing Scheirer's beat detection algorithm [5] for heartbeat detection and localization, efficient signal substitution, and signal re-combination. The quantitative analysis was performed to address these focus areas of the model. The analysis also used simulated signals as input into the heartbeat detection and localization algorithm, and continuing through the pathology substitution and heart sounds/lung sounds signal re-combination portions of the model. A comparison of a combination of the input of a simulated heart sound and lung sound signal was made to the resulting modified and combined heart and lung sound signal. From a visual inspection, it could be seen that the location of the adjusted signal was not an exact match to the location of the first heartbeat of the reference signal, but that the locations were fairly close. The calculated heart rate of both reference and modified signals showed a very good correlation in rate. Visually, it could be seen that the amplitude and shape of the original and combined signals are comparable. In

addition, the beat locations of the adjusted signal combination did not perfectly align with the beat locations of the reference combination. Since the idea is to present a modified version of a patient's signal back to listener, the location of the heart beats is not as important as the signal possessing an accurate heart rate, and adequately including abnormal pathology in way to sound realistic to a listener.

Another portion of the quantitative assessment included applying the complete model to the simulated input signals, with the output of the signal separation being used for the input to the signal modification. The beat locations of the adjusted signal combination did not perfectly align with the beat locations of the reference combination. However, the adjusted signal combination did closely resemble the reference combination in heart rate. However, visually, the signal did resemble the original combined signal with a proper adjustment to heart rate. Overall, the results of applying the complete model to a set of simulated signals was successful. The results do correspond to the preliminary results of the qualitative assessment, which utilized real heart sound and lung sound signals.

In addition, both a qualitative assessment of the final modified output of the model was conducted. The assessment included both visual and auditory analysis. The assessment signal set contained various signals including the original heart sounds and lung sounds signals, pathological heart and lung sound signals, combined (without heart sound adjustment) original and pathological signals, and combined (adjusted heart sound) original and pathological signals. Preliminary SME analysis identified model output signals that exhibited both visual and auditory realism. The results from an additional assessment were presented. Out of eight signals four were deemed correct. One signal

was deemed incorrect and three signals received an inclusive assessment due to a possible artifact. For the signals with favorable assessments, there seem to be a common characteristic of a difference in amplitude of the heart sounds and lung sounds, with the lung sounds being too loud or the heart sounds needed to be louder.

5.3 Discussion of Results

A discussion of the results is presented. The quantitative analysis did show that the heart rate was accurately detected. Though the analysis highlights that the heartbeat locations of the modified and reference signals did not perfectly align, it is thought that this difference is acceptable due to the fact that the signals are different in their structure, but more importantly, the modified signal as a whole does align closely with the reference signal. It is thought that the signals would be more of a continuous nature and the initial location is not as important as matching the heart rate, which will be pertinent throughout the entire signal presentation to the medical student.

Much weight is given to the qualitative assessment, as the ultimate goal of the model is to provide accurate and efficient signal modification for presentation to medical student via a modified stethoscope. The ultimate test is auditory realism by a medical student to detect an abnormality in heart or lung sounds. For the output modified signal of the model to pass this test, then the various stages of the model including heart and lung sound signal separation, input signal characterization, signal modification and signal re-combining must each provide accurate results.

This dissertation has made the following contributions:

1. Applied the de facto standard tempo and beat detection algorithm developed by Eric Scheirer [5] to heart signal analysis in order to detect heart rate and location of heartbeats in a heart sound signal.
2. Utilized the algorithm to characterize separated heart sound signals (input) and reference pathology signals in order to modify the reference signal to better match the input signal in terms of heartbeat rate and location of the heartbeats.
3. Utilized the algorithm to verify the heartbeat rate of the adjusted signal.
4. Implemented Scheirer's algorithm [5] in MatLab, with only minor changes, such as adjusting the ranges of the six frequency bands.
5. Investigated techniques for modifying and substituting real heart and lung pathology signals in real-time.

5.4 Recommendations

The research, which focused on developing and validating the presented signal analysis and modification model for real-time virtual pathology, has proven very successful.

However, for further research to be conducted in the future, various improvements related to each portion of the model have been identified to improve the accuracy, robustness, and possibly efficiency of the model. For the WTC-ANC filtering, for production, it is strongly suggested that the MatLab WT-ANC implementation is replaced with a custom implementation. This will improve performance as related to accuracy and efficiency.

With regards to heartbeat detection and localization, there is a recognized need for a detailed assessment of fine-tuning the heartbeat detection and localization algorithms.

This is needed to fully understand the cause of the error in the location calculation and investigate a solution to improve the accuracy. For pathology substitution, there is a recognized need to investigate developing more sophisticated methods for adjusting signals based on signal characteristics identified with the heartbeat detection and localization algorithm. This should include investigating if there is a need for and if so, developing methods for adjusting lung sound signals to substitute abnormal lung sound signals for presentation to a student. To improve the signal recombination portion of the model, there is a need to investigate more advanced, robust and accurate methods for combining signals. These methods would better support processing signals having different characteristics, including different sampling rates. The methods would also better support signals with a broad range of characteristics, including signals being acquired under varying conditions, such as the gain settings on a modified stethoscope, and other data formats besides WAV files.

5.5 Possible Applications

The methods and algorithms, addressed in this research, are specific to the real-time modeling of human body sounds. A model was developed to use a heart/lung sound signal as input, locate and separate the heart sound signal from the lung sound signal, modify the heart sound signal or lung sound signal by adding an abnormality such as a crackle or wheeze, respectively, and then providing output of a reconstructed modified signal. The intent is for the model to be used in an application involving the augmentation of medical equipment with pathological sounds to be used with virtual patients for training medical students.

A description of a possible application is shown in Fig. 47. It is anticipated that additional research outside of this dissertation study would be required to finalize the architecture and confirm its viability. The system would be capable of providing fine crackle and additional abnormalities, without requiring an SP to manually control when sounds are heard. The system would incorporate the real-time modification of SP heart/lung sounds with signals that include various heart abnormalities.

The proposed notional system, shown in Fig. 54., includes the signal analysis and modification being performed in a remote computer. The SP heart and lung sound signals would be acquired with a modified stethoscope. The signals would then be transmitted to a remote laptop, using the transmission methods previously used by McKenzie, *et al.* [3] or via something comparable to BlueTooth™. Investigation would be needed to determine the most efficient method. Efficiency is important to minimize the delays that would occur for bi-directional transmission of the signal and the signal modification, which would occur after the head of the modified stethoscope is moved over an appropriate area. The signal modification would include applying the WT-ANC filtering technique to the signal, applying the heartbeat detection and localization to the separated heart sound signal, adding an abnormal heart sound signal or lung sound signal and then recombining and transmitting back to the stethoscope for presentation to the student in an efficient and real-time manner. While the system depicts an application where the model is executed on a computer with a wireless connection to a modified stethoscope, the presented model could certainly be enhanced for efficiency and integrated with the modified stethoscope to reduce latency for presentation of the modified signal to the user.

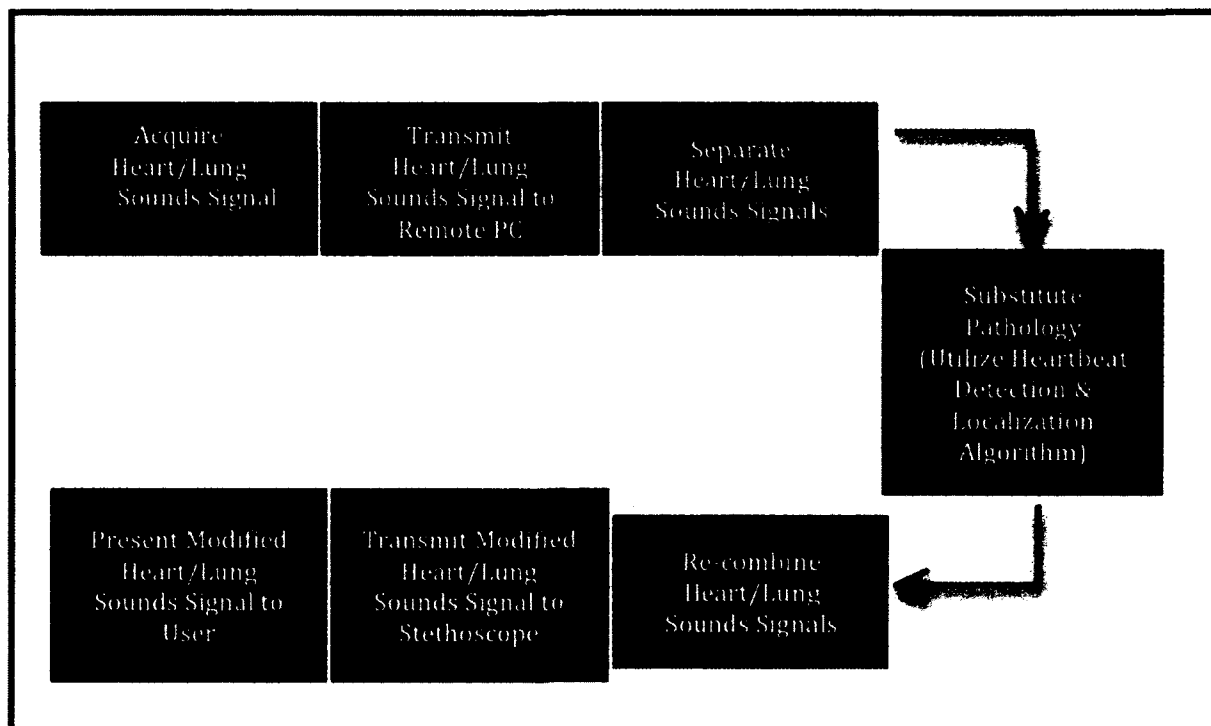


Fig. 54. Proposed system with remote signal modification.

While the system depicts an application where the model is executed on a computer with a wireless connection to a modified stethoscope, the presented model could certainly be enhanced for efficiency and integrated it the modified stethoscope to reduce latency for presentation of the modified signal to the user.

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APPENDICES

APPENDIX A: DESCRIPTION OF INPUT AND REFERENCE HEART/LUNG SIGNALS

The files containing ECG and sound signals were provided by personnel from the Medical Imaging Diagnosis and Analysis Laboratory of Old Dominion University Dominion. The signals, which are listed below, were collected from the pulmonary region. The Welch Allyn Meditron™ electronic stethoscope was used to gather the data. All the signals were collected using conductive gel which reduced the noise and leads to a better signal acquisition. The stethoscope built-in filter was set to L: low frequency, M: medium frequency or H, high frequency to gather the cardiological sounds only. The signals were collected for 15.5-seconds.

I. Breathing Condition Data

- Sampling rate: 44.1 KHz
- Collection date: September 28, 2010.
- File format: BreathingCondition
 - BreathingNormal.WAV
 - DeepBreathing.WAV
 - HoldingBreath.WAV

II. Aortic Data

- Collection device: Welch Allyn Meditron™ electronic stethoscope system
- Data: channel 1: ECG, channel 2: Heart sounds
- Sampling rate: 44.1 KHz
- Collection date: October 12, 2010.
- Stethoscope filter: Low, middle and high frequency

- Auscultation Area: Aortic region
- File format: Stethoscope Gain_Breathing Condition_#
 - Low_Deep_01.WAV
 - Low_Deep_02.WAV
 - Low_Holding_01.WAV
 - Low_Holding_02.WAV
 - Low_Normal_01.WAV
 - Low_Normal_02.WAV
 - Middle_Deep_01.WAV
 - Middle_Deep_01.WAV
 - Middle_Holding.WAV
 - Middle_Normal.WAV
 - High_Deep.WAV
 - High_Holding_01.WAV
 - High_Holding_02.WAV
 - High_Normal_01.WAV

II. Standard Patient Auscultation Area: Aortic, Pulmonic, Tricuspid, and Mitral

- Collection device: Welch Allyn Meditron™ electronic stethoscope system
- Data: channel 1: ECG, channel 2: Heart sounds
- Sampling rate: 44.1 KHz
- Collection date: October 21, 2011.
- Stethoscope filter: low frequency to collect heart sounds only
- File format: Auscultation Area_Breathing Condition
 - Aortic_normal_breathing.WAV
 - Aortic_holding_breath.WAV
 - Aortic_breathing_heavily.WAV
 - Pulmonic_normal_breathing.WAV
 - Pulmonic_holding_breath.WAV
 - Pulmonic_breathing_heavily.WAV
 - Tricuspid_normal_breathing.WAV

- Tricuspid_holding_breath.WAV
- Tricuspid_breathing_heavily.WAV
- Mitral_normal_breathing.WAV
- Mitral_holding_breath.WAV
- Mitral_breathing_heavily.WAV

III. Auscultation Area: Pulmonic Region

- Collection device: Welch Allyn Meditron™ electronic stethoscope system
- Data: channel 1: ECG, channel 2: Heart sounds
- Sampling rate: 44.1 KHz
- Collection date: November 07, 2011.
- Stethoscope Amplification: Low, Medium (Mid), High
- File format: Auscultation Area_Stethoscope Filter Setting_Breathing Condition
 - Pulmonic_low_holding_breath.WAV
 - Pulmonic_low_Breathing_heavily.WAV
 - Pulmonic_low_Normal_Breathing.WAV
 - Pulmonic_mid_holding_breath.WAV
 - Pulmonic_mid_Breathing_heavily.WAV
 - Pulmonic_mid_Normal_Breathing.WAV
 - Pulmonic_high_holding_breath.WAV
 - Pulmonic_high_Breathing_heavily.WAV
 - Pulmonic_high_Normal_Breathing.WAV

IV. Pathology

- Sampling rate: 8 KHz
- Collection date: November 24, 2003.
- File format: Heart/Lung Characteristic
 - STG_HeartS_EjectionMurmur.WAV
 - STG_LungS_Asthma.WAV
 - STG_LungS_CHF_Crackles.WAV
 - STG_LungS_Norm_Tracheal.WAV

**APPENDIX B: QUESTIONNAIRE FOR QUALITATIVE ASSESSMENT
OF MODIFIED HEART SOUND AND LUNG SOUND SIGNALS**

List of questions appearing in the questionnaire:

- | | | | | | |
|--|----------|----------|-------|----------------|--|
| 1) The sound is realistic. | | | | | |
| Strongly Disagree | Disagree | Not Sure | Agree | Strongly Agree | |
| 2) There are no artifacts in signal. | | | | | |
| Strongly Disagree | Disagree | Not Sure | Agree | Strongly Agree | |
| 3) The timing of the pathology is correct. | | | | | |
| Strongly Disagree | Disagree | Not Sure | Agree | Strongly Agree | |
| 4) Additional Comments. | _____ | | | | |
| | _____ | | | | |
| | _____ | | | | |

VITA

Dennis L. Bergin has previously earned an M.S. in computer engineering from The Johns Hopkins University, located in Baltimore, MD in 1992 and a B.S. in computer science from the University of Maryland Baltimore County, located in Baltimore, MD in 1989. Mr. Bergin has the following certifications and training, Project Management PMP training completed Feb 2012 (Planned PMP certification exam September 2012), ITIL v3 Foundations Course and Certification Exam, March 2012, and MSEM Engineering Management Continuing Studies, The George Washington University, 2002 – 2005, and MSEE Communications Continuing Studies, The George Washington University, 1995 – 2002.

He is currently a Principal Engineer at Invertix Corp. located in McLean, VA, providing expertise in mobile platform computing, (Android, iOS), cloud computing, service oriented architectures, advanced human computer interfaces, and intelligence community enterprise architectures, including web services, widgets, widget frameworks and mashups, search and indexing. In addition he operates his own consulting company, Allied Forces Solutions, located in Vienna, VA, providing embedded software design/development expertise for various robotics, communications and modeling and simulation applications. He is listed as a co-inventor on patent related to “Independently Acquiring and Tracking Communication System Signaling Channel Assignments on Communication Links,” a co-author on the SIW Paper on the Matrix Mapping Tool 05F-SIW-12, and a co-author on the SIW Paper on Development of a Communications Effects Server Framework 06S-SIW-038.