

A Stethoscope with Wavelet Separation of Cardiac and Respiratory Sounds for Real Time Telemedicine Implemented on Field-Programmable Gate Array

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ABSTRACT

Auscultation is one of the most utilized physical examination procedures for listening to lung, heart and intestinal sounds during routine consults and emergencies. Heart and lung sounds overlap in the thorax. An algorithm was used to separate them based on the discrete wavelet transform with multi-resolution analysis, which decomposes the signal into approximations and details. The algorithm was implemented in software and in hardware to achieve real-time signal separation. The heart signal was found in detail eight and the lung signal in approximation six. The hardware was used to separate the signals with a delay of 256 ms. Sending wavelet decomposition data —instead of the separated full signal— allows telemedicine applications to function in real time over low-bandwidth communication channels.

Keywords: Auscultation, discrete wavelet transform, FPGA, heart sounds, lung sounds.

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1. INTRODUCTION

Auscultation is a physical examination procedure, which is one of the most commonly utilized in routine consults and emergencies and which can provide initial information on patient health. The most common method for performing auscultation is through a stethoscope, which allows one to listen to heart, lung and intestinal sounds. Possible disease detection depends on the experience of the physician performing the procedure. Wherever the stethoscope is placed on the body, it will pick up sounds from the previously mentioned organs with varying intensities, along with ambient sounds, making it difficult to detect a condition that the patient may present.

Heart sounds or noises are produced by cardiac valve closure (Figure 1). The aortic and pulmonary valves open when the ventricles contract to expel blood into the arteries, while the atrioventricular valves, i.e., the mitral and tricuspid valves, close to prevent the backflow of blood into the atria. This produces the first heart sound, called S1. When the semilunar valves, i.e., the aortic and pulmonary valves, close and the mitral and tricuspid valves open to fill the ventricles with blood from the atria, the second sound, called S2, is produced. The S1 and S2 noises aid in the diagnosis of cardiac muscle disease. The S1 sounds have a frequency of 20-150 Hz, and the S2 sounds have a frequency of 50-60 Hz. Other noises that can be heard are the third (S3) and fourth (S4) sounds, which can arise from vibrations at the beginning and end of diastole. Respiratory noises are caused by air flowing through the airways, resulting in turbulence and vibrations.¹ The noises are auscultated throughout the entire inhalation and exhalation cycle, and a separation between the two phases occurs when the flow decreases and falls to zero,² as shown in Figure 2. The respiratory sounds range in frequency from 100-1600 Hz.



Figure 1 Normal cardiac sounds. S1 (mitral and tricuspid valve closure), S2 (aortic and pulmonary valve closure), S3 (ventricular filling vibration) and S4 (atrial contraction) [1].

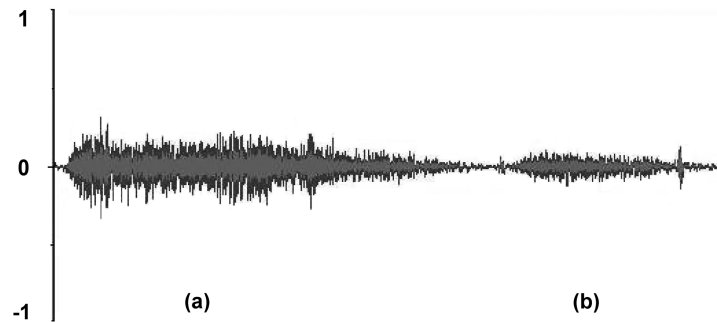


Figure 2. Respiratory signal.

During auscultation of the thorax, the pulmonary and heart sounds overlap in both time and frequency. Therefore, conventional filters fail to correctly separate the two signals. The challenge is to separate the two sounds without affecting their integrity.

In areas devoid of medical specialists, telemedicine services can improve the quality of health services.³ Remote monitoring, specifically from fixed points (e.g., the home or hospital) or wirelessly, has undergone significant development in recent years.⁴⁻⁸ In the case of auscultation, new developments have been made in digital stethoscope applications, in both those used at home and mobile devices.⁹⁻¹³ The digital stethoscope developed by Hung¹⁰ included a feature that separates sounds using adaptive filters implemented in embedded systems. Sound quality is fundamental for the performance of remote auscultations, in which the physician is not at the patient's side. Therefore, the possibility of separating and transmitting a particular sound could improve the quality of the diagnosis. However, limitations to the communication channels available at remote sites warrant the development of a system that decreases the amount of data transmitted in order to use these devices over low-bandwidth communication channels.

The development of electronic stethoscopes has provided several solutions for obtaining improved audio signals (e.g., eliminating ambient noise). Different types of algorithms have been utilized to process auscultation signals, both to reduce noise and to isolate the heart signal (and eliminate the respiratory sounds), such as in the case of adaptive filtering¹⁴⁻¹⁶ and statistical filtering.¹⁷ Independent component analysis (ICA) has been utilized to separate pulmonary and heart sounds;^{18, 19} however, this method requires signals from at least two stethoscopes placed in different locations, which is impractical in a routine clinic. Likewise, frequency modulation filters and discrete wavelet transform (DWT) with multi-resolution analysis^{20, 21} have been used.

The purpose of this study was to develop a digital stethoscope capable of separating and transmitting heart and respiratory sounds in real time using low-bandwidth communication channels.

2. MATERIALS AND METHODS

The study was divided into the following three stages: 1) definition of the separation algorithm; 2) implementation of the algorithm on a personal computer (PC); and 3) implementation of the algorithm on a Field Programmable Gate Array (FPGA) platform

Sounds were captured with the bell of a Mark of Fitness conventional stethoscope (Nihon Seimitsu Sokki Co, Japan), for which was adapted a microphone with the following characteristics: omnidirectional, -58 dB sensitivity, 2.2 k Ω impedance, 5-10 V operating voltage and cylindrical shape (6 mm in diameter by 6 mm in height).

To implement the algorithm on a PC, a Dell Precision 390 workstation (Dell Computer Corporation, Round Rock, TX, USA) running Matlab 2009a software (The Mathworks, Natick, MA, U.S.A.) was used to capture the sounds from the microphone (from the PC sound card) and to perform sound separation using the Wavelet Toolbox functions (Figure 3).

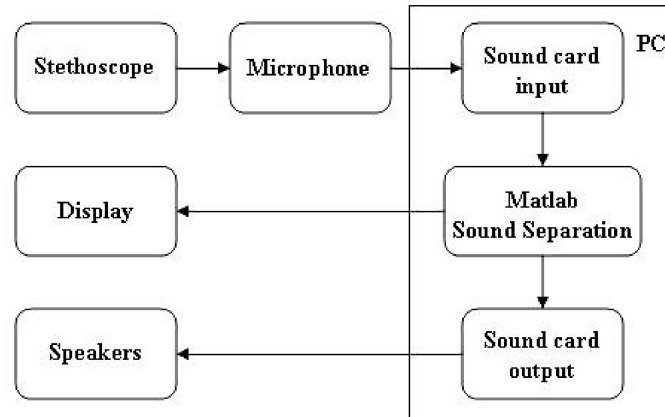


Figure 3. Diagram of acquisition and analysis with a PC equipped with Matlab.

The analog-to-digital conversion (ADC) of the signal from the microphone and the execution of the DWT separation algorithm—which involves many addition and multiplication operations with decimal coefficients—generates a substantial delay for real time applications during the hardware implementation via sequential devices (e.g., microprocessor, microcontroller). Therefore, a FPGA platform was chosen.

For the hardware implementation (Figure 4), we used the Nexys II Development Board (Digilent Inc., WA, U.S.A.), which has a FPGA (XC3S1200E) and several general-purpose ports. This FPGA family consists of up to 2 KB of dual memory and 18-bit asynchronous and synchronous multipliers. This Development Board lacks ADC converters, so a microphone polarization circuit, a microphone signal-conditioning circuit, and an 8-bit ADC (ADC0820) were added to capture the microphone signal. An R2R digital-to-analog circuit and an instrumentation amplifier (INA620) were included to reproduce the separated sounds.

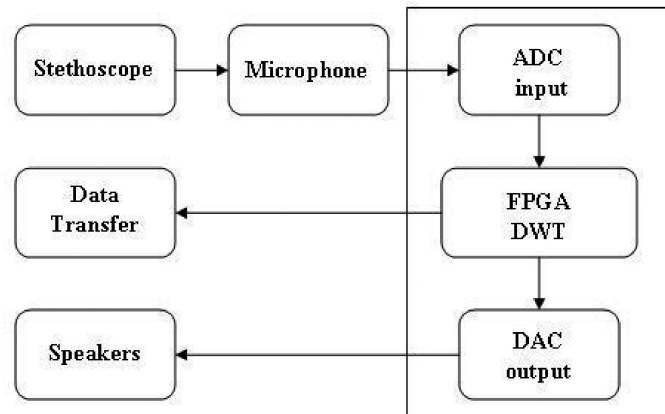


Figure 4. Diagram of the acquisition and analysis with FPGA.

2.1. Separation algorithm

For signal separation, an algorithm based on DWT with multi-resolution approximation was developed.^{21, 22} The wavelet transform separates the signal in the time and frequency domains. The family of functions used to represent the transformed wavelet signals, called $Wf(u, s)$, is generated through a normalized mother function ψ with a mean value of zero, in which dilations (s) and translations (u) are performed.²² The $Wf(u, s)$ transform is defined by the equations (1) and (2).

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-u}{s}\right) \quad (1)$$

$$Wf(u,s) = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{s}} \psi_{u,s}^*(t) dt \quad (2)$$

A multi-resolution approach is utilized in order to minimize the number of scales required, separating the signal into two signals: one of approximation and another of detail. A set of discrete conjugate filters was selected for this purpose,²² where $s = \left\{ 2^{j/2} \right\}_{j \in \mathbb{Z}}$, which forms a family of orthogonal bases. Thus, the new expression for the transform is

$$Wf(u, 2^{j/2}) = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{2^{j/2}}} \psi_{u, 2^{j/2}}^*(t) dt. \quad (3)$$

It is possible to create different levels of decomposition according to the nature of j . If j is negative, the details are obtained; on the other hand, if j is positive, approximations are obtained. This algorithm can be implemented for signals at discrete times utilizing the orthogonal fast wavelet transform.²² In multi-resolution analysis, the signal is separated into the following two parts: a) *the approximation*, obtained from the inner product between the function and the scaling function, i.e., $a_j[n] = \langle f, \phi_{j,n} \rangle$ and b) *the detail*, obtained from the inner product between the function and the wavelet function, i.e., $d_j[n] = \langle f, \psi_{j,n} \rangle$. The theorem developed by Mallat²² demonstrates that each point p in the approximation $a_j[p]$ and detail $d_j[p]$ at a decomposition level j can be calculated through a discrete convolution followed by a subsample, as

$$a_{j+1}[p] = \sum_{n=-\infty}^{+\infty} h[n-2p] a_j[n] = a_j * \bar{h}[2p] \quad (4)$$

and

$$d_{j+1}[p] = \sum_{n=-\infty}^{+\infty} g[n-2p] a_j[n] = a_j * \bar{g}[2p] \quad (5)$$

where h is a low-pass filter and g is a high-pass filter. The j -level approximation reconstruction $a_j[n]$ is obtained by (6).

$$a_j[n] = \sum_{k=-\infty}^{+\infty} \overset{\circ}{h}[n-2k] a_{j+1}[k] + \sum_{k=-\infty}^{+\infty} \overset{\circ}{g}[n-2k] d_{j+1}[k] \quad (6)$$

where $\overset{\circ}{h}$ is a low-pass filter and $\overset{\circ}{g}$ is a high-pass filter. In reconstruction process when n is even only even coefficients are used; similarly, when n is odd only odd coefficients are used.

2.2. Selection of the wavelet function

To obtain the filter bank, the scaling function or wavelet for separation should first be selected. The selection criteria depend on the regularity of the function f , the number of vanishing moments and the size of its support.²² Scaling functions include the Haar, Daubechies, and Symlets functions shown in Figure 5. The vanishing moments determine the finer details that can be represented in a wavelet transform application. The Daubechies and Symlets functions were utilized because of their similarity to heart noises.

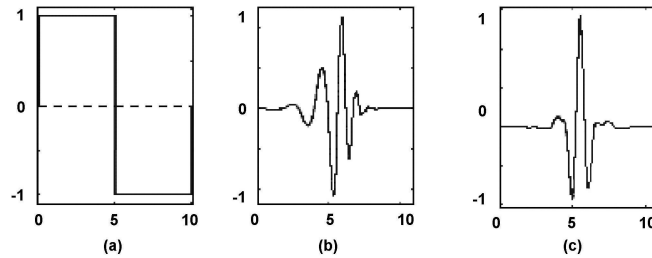


Figure 5. Wavelet functions. a) Haar, b) Daubechies (p=6), c) Symlets (p=6).

2.3. Implementation in Matlab

The PC sound card was used to acquire auscultation data from different healthy individuals ranging from 18-25 years of age. The data collection was performed at a sampling rate of 8 kHz at 8 bits. Two programs were run in Matlab, one with Wavelet Toolbox functions (dwt and idwt) and another for the multiplication and addition cycles. The first program detected the level of decomposition required to separate the heart and respiratory sounds. A diagram of the algorithm for decomposing the signal into the approximation and detail is presented in Figure 6. A signal reconstruction diagram is shown in Figure 7. To determine the decomposition level required, reconstructions at different levels were performed until no variations were found between two consecutive decompositions. Additionally, the separated signals were compared to the expected respiratory and heart signals. The second program, based on multiplication and addition cycles, permitted testing of the algorithm for subsequent hardware implementation on the FPGA.

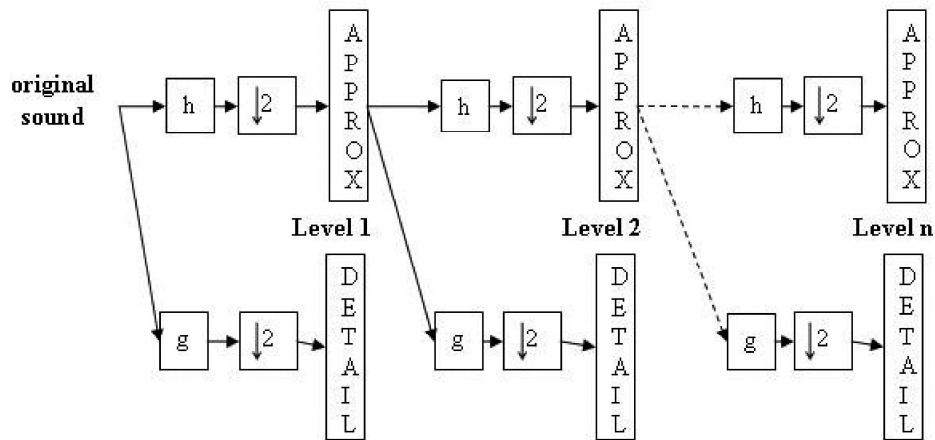


Figure 6. Diagram of the signal decomposition algorithm in Matlab.

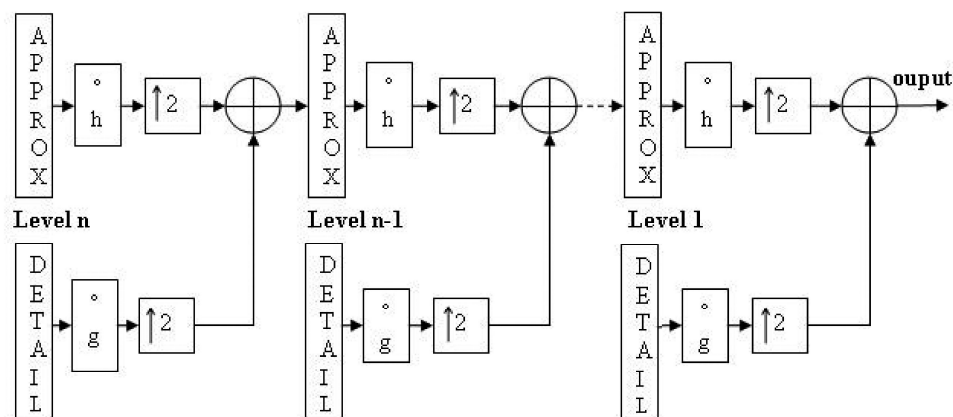


Figure 7. Diagram of the signal reconstruction algorithm in Matlab.

2.4. Implementation on the FPGA

The decomposition and reconstruction algorithms used convolutions based on sums and products with coefficients varying between -1 and 1, which were obtained using the Matlab `wfilters('sym8')` function (Table 1). Fixed-point libraries were used to facilitate working with the sums and signed products. The FPGA platform includes 18-bit multiplier modules. The coefficients were quantized in 13 bits (2 integer bits and 11 decimal bits) in fixed-point. The signal was normalized to values between 1 and -1 and quantized in 18 bits (7 integer bits and 11 decimal bits). The overall process was controlled with a state machine.

The separation process (Figure 8) is performed as follows: a set n of samples is collected and stored in the M1 memory, and the process of decomposition is initiated; data in the first memory (M1) are read and the convolution is calculated, i.e., all data are multiplied in parallel by the filter coefficients; the individual results products are added and stored in the next memory (M2); this continues with the convolution of M2 memory data and its collection in the next memory (M3), continuing until a final decomposition level in which the selected signal (i.e., heart or respiratory) is identified.

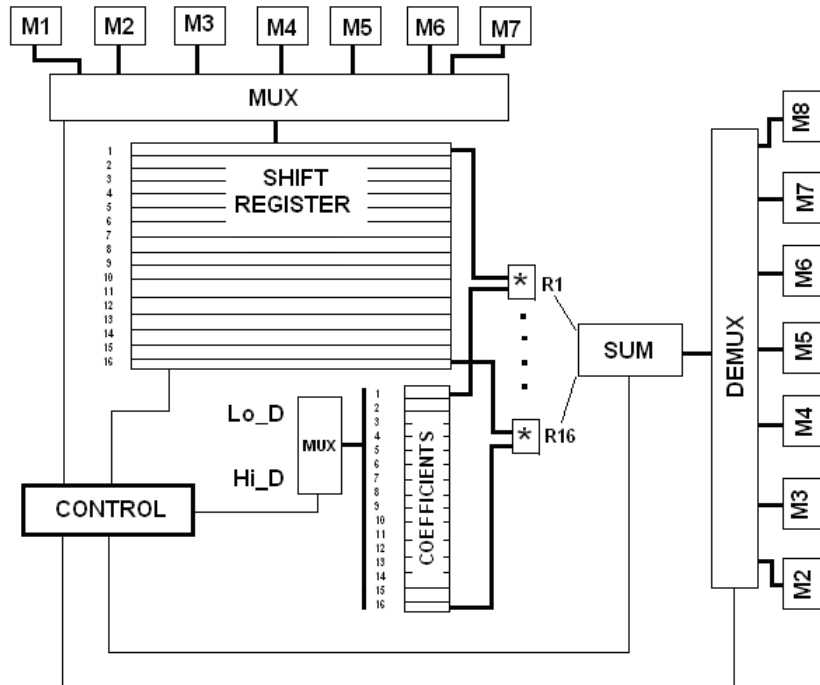


Figure 8. Diagram of the signal decomposition algorithm with FPGA.

The reconstruction algorithm doubles the quantity of data being reconstructed from the previous level. For the selected signal the reconstruction process (Figure 9) is performed after the final decomposition as follows: the last memory utilized in the final decomposition is read and the convolution is calculated, i.e., two parallel multiplications are performed between level data and coefficients, one for even coefficients and another for the odd coefficients, as stated in (6); the sum result is stored in the next data memory (i.e., this one after the final decomposition level memory). This process is repeated successively with each level memory, until arriving at the reconstruction of the signal.

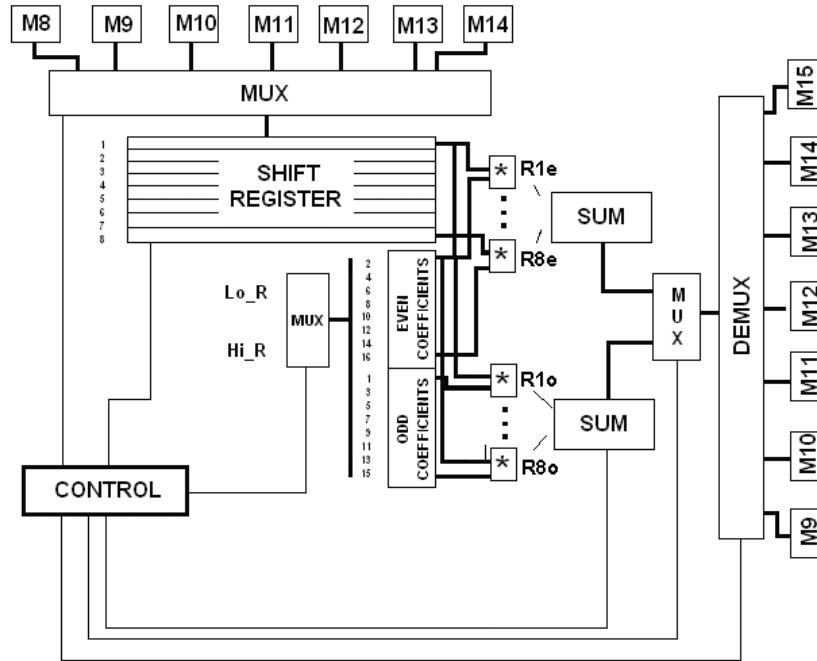


Figure 9. Diagram of the signal reconstruction algorithm with FPGA.

Table 1. Coefficients of the Symlets filter bank obtained with Matlab.

	Decomposition		Reconstruction	
	High-pass h	Low-pass g	High-pass \hat{h}	Low-pass \hat{g}
1	-0.0019	-0.0034	-0.0034	0.0019
2	-0.0003	-0.0005	0.0005	-0.0003
3	0.015	0.0317	0.0317	-0.015
4	0.0038	0.0076	-0.0076	0.0038
5	-0.0491	-0.1433	-0.1433	0.0491
6	-0.0272	-0.0613	0.0613	-0.0272
7	0.0519	0.4814	0.4814	-0.0519
8	0.3644	0.7772	-0.7772	0.3644
9	-0.7772	0.3644	0.3644	0.7772
10	0.4814	-0.0519	0.0519	0.4814
11	0.0613	-0.0272	-0.0272	-0.0613
12	-0.1433	0.0491	-0.0491	-0.1433
13	-0.0076	0.0038	0.0038	0.0076
14	0.0317	-0.015	0.015	0.0317
15	0.0005	-0.0003	-0.0003	-0.0005
16	-0.0034	0.0019	-0.0019	-0.0034

3. RESULTS AND DISCUSSION

Although the Daubechies wavelet function greatly resembles the heart signal, the Symlets function offered better separation. Using the program developed in Matlab, the respiratory signal was found in the reconstruction of approximation six, and the heart signal was found in the reconstruction of detail eight. The reconstruction of a decomposed signal requires a minimum of 16 data points. Because each level of decomposition produces half the amount of data as the previous level, the algorithm was adjusted to collect 1024 data points from the original signal before beginning the decomposition process. At a sampling frequency of 4 kHz, the first 1024 data points from the original signal were collected in 256 ms, producing a slight delay. The heart signal at level 8 was composed of 27 data points, whereas the respiratory signal was composed of 96 data points (of the 1024 data points from the original signal collected over 256 ms).

An example of the result obtained using Matlab can be seen in Figure 10. In the original signal, the components of the heart signal and ambient noise were mixed with the pulmonary signal (Figure 10a). Upon applying the algorithm, the heart signal could be observed with the noise components (Figure 10b) and the pulmonary signal with the heart noise present (Figure 10c).

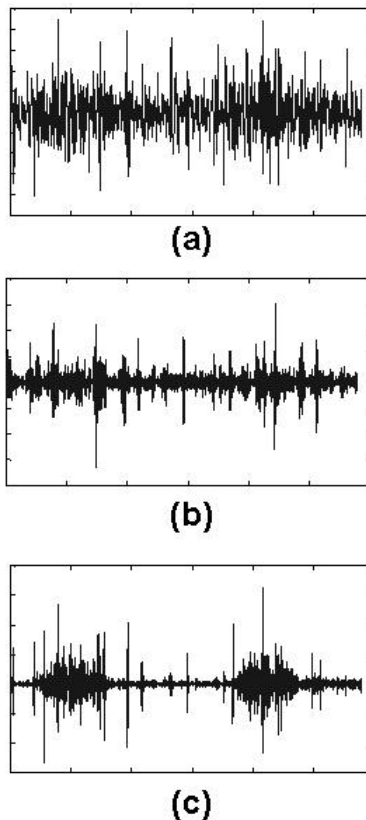


Figure 10. Signals processed with a PC. a) Audio signal captured with the PC sound card. b) Heart signal separated with Matlab. c) Respiratory signal separated with Matlab.

In the FPGA, the time required to perform the 8-level decomposition and reconstruction processes was 200 μ s. Because the signal sampling frequency was 4 kHz (period of 250 μ s), there was sufficient time to prevent sample loss during each process of decomposition and reconstruction. This, added to the initial delay of 256 ms, can be considered real time. The space occupied in the FPGA was approximately 20%, involving 1144 *slices*, 15 dual RAM memories, and 28 multipliers. An example of the signal separated by FPGA is shown in Figure 11.

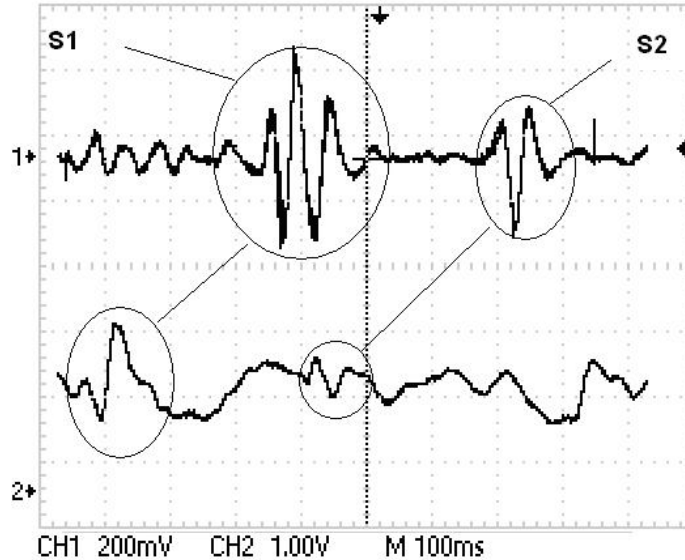


Figure 11. An audio heart signal separated using the hardware.

The algorithm permits effective acquisition of the separated audio heart signal with good audio quality. However, because the samples were taken at a fixed rate of 4 kHz and because the wavelet algorithm provides an output at the same rate, there was no real decrease in the bandwidth required for transmission when the reconstructed signal was transmitted without any type of compression using an audio transmission encoder (i.e., 64 kb/s). Because the reconstructed signal (respiratory or heart) contained less information—due to the separation—better compression rates could be achieved than if the original signal were compressed without separation. For example, after applying MPEG-1 Audio Layer III compression (better known as MP3) to the original and separated signals, a 30% increase in the compression rate was achieved for the separated signal.

Another alternative exists for further reducing the bandwidth required: instead of sending the separated signal, approximation six, for the respiratory signal, and detail eight, for the heart signal. Further, the reconstruction is accomplished at the reference site. Thus, for every 1024 data points in the original signal, only the 27 data points constituting the heart signal or 96 data points composing the respiratory signal are sent, which would correspond to a greater compression rate than that achieved by encoders like MP3. This clearly requires two FPGA (one at each end of the communication channel) but permits the use of lower cost communication channels. The heart signal data encoded in two bytes can be transmitted at 1.69 kb/s, along with the respiratory signal data at 6 kb/s. These low rates are readily available through modem with a dial-up or through a shared internet connection.

The patients' variability may affect the approximation and detail level at which the separation signal can be detected. This problem, however, can be handled by a decomposition–reconstruction iterative algorithm, so that at each iteration level the coefficients are compared with a statistical threshold proportional to the standard deviation of the transform. This threshold determines whether signal components are stationary or not. In the first case, wavelet coefficients have lower values and components belong to the lung sound. In the second case, coefficients are higher and they belong to the heart sound.²³ This algorithm may be also easily implemented in a FPGA.

Finally, electrical safety tests were performed with a Fluke ESA601 (Fluke Biomedical, Everett, WA, USA) electrical safety analyzer and radiated emissions testing (in an anechoic chamber between 20–1000 MHz), revealing that the device met the respective standards (IEC 60601 and CISPR 11) according with the protocols established in our laboratory.²⁴

4. CONCLUSION

Implementation of the separation algorithm for heart and respiratory sounds was achieved in real time. The wavelet filters allowed adequate separation of the signals from normal patients. These signals could be transmitted remotely, sending only the decomposition data, and reconstructed at the remote reference site. This does not require very high

bandwidth, and thus, telemedicine applications may be implemented in real time at low cost. In the future, we will work with patients with different diseases to determine the diagnostic accuracy achieved with this device.

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