Wireless PC-based Phonocardiograph and Diagnosis

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Abstract

Auscultation is used to evaluate heart health and can indicate when it's needed to refer a patient to a cardiologist. Advanced PCG signal processing algorithms are developed to assist the physician in the initial diagnosis but they are primarily designed and demonstrated with research quality equipment. Therefore there is a need to demonstrate the applicability of those techniques with consumer grade instrument. Furthermore, routine monitoring would benefit from a wireless PCG sensor that allows continuous monitoring of cardiac signals of patients in physical activity, e.g., treadmill or weight exercise. In this work, a low-cost portable and wireless healthcare monitoring system based on phonocardiograph signal is implemented to validate and evaluate the most advanced algorithms. Off-the-shelf electronics and a notebook PC are used with MATLAB codes to record and analyze PCG signals which are collected with a notebook computer in tethered and wireless mode. High valued diagnostics based on the S1 and S2 signals and MATLAB codes are demonstrated. While the prototype is based on MATLAB, the later is not an absolute requirement.

Keywords: *Auscultation, S1, S2, Heart sounds, Wireless Phonocardiogram, Signal processing, Diagnostic parameters*

1. Introduction

The electrocardiogram (ECG) is a popular method for checking anomalies of cardiorespiratory function over many decades and it works by keeping track of electrical heart activity. However, heart defects may be caused by structural abnormalities and therefore are more likely to produce vibromechanical indicators aside from electrical ones. For that example, heart auscultation is more useful than ECG for characterizing murmurs and other abnormal heart sounds. Heart sounds convey important physiological and pathological information. The heart murmurs caused by turbulent blood flow and anomalous valve opening or closing, can be noticeably detected by trained ears when adequate sensors are used. While auscultation is useful, detection of cardiac signatures via auscultation demands extensive physician's experience, whether with an analog acoustic or electronic stethoscope. It is desirable to equip primary care physicians that do not have extensive auscultation skills with a diagnostic tool so they screen patients for referable conditions. It may also be beneficial for general users, patients and front line care givers to perform auscultation at home and to continuously monitor sporadic symptoms that may not be detected during periodical medical visits. Furthermore, the convenience of a sensor not tethered to the recording PC allows continuous monitoring in many relevant scenarios, for example, with the subject doing treadmill or weight lifting exercises. Therefore, an automated and wireless system to detect and characterize heart sounds is explored in this paper. Variance of PCG quality, whether due to electronic specifications of the sensor, the placement of the stethoscope on the chest and the additional noise introduced by the wireless operation are seen as major challenges on the sensor side. On the signal processing side, we would like to show that the advanced PCG algorithms can be implemented on a modest computing platform. The goal of the paper is to report the implementation of a simple wireless PCG sensor designed to operate with a notebook or tablet computer, and signal processing that minimizes the effects of the varying electronic performance and stethoscope's placement. The segment of users targeted by this sensor consists of primary care physicians and care givers. Therefore, the key requirements are robust processing algorithms immune to the mentioned variances, informative indicators and rudimentary classification of heart sounds to assist users in choosing the next action.

An essential function of the PCG signal processing is the extraction of the first heart sound (S1) and second heart sound (S2). A survey of heart sound segmentation techniques based on the extraction of the waveform envelope was conducted by Choi in [Choi & Jiang,2008]. The paper evaluated the extraction techniques which are based on the Shannon energy envelope, Hilbert transform, and characteristic waveform extraction. A more recent evaluation of envelope extraction algorithms was reported by Liu in [Liu et al., 2011]. A novel technique developed and reported by Barabasa [Barabasa, Jafari, & Plumbley, 2012] has been proven to be insensitive to performance degradation and noise interference, a potential major issue for wireless sensors and recording during physical activity. The algorithm is also robust with respect to pathological signals such as heart murmurs. It is based on a musical analysis application, particularly known for its ability to track beats in the presence of noisy and varying background. We adopted the technique of dynamic programming for beat tracking published by Ellis [Ellis, D. P.W., 2007]. Robust segmentation of the heart sounds is only the first step in classifying heart sounds. It's proposed that diagnostic parameters [Choi & Jiang, 2005] which are derived from the heart sounds and cardiac waveform can be used for cardiac classification. Our goal is to demonstrate that useful parameters can be derived from the heart sounds and presented to the users for screening diagnostic purposes.

Most medical algorithm development works are reported without implementation details. That makes it difficult to estimate the effort requires to transition research knowledge to commercial realization. In this paper, we will make an effort to trace the lineage of the open source codes, describe the techniques in sufficient details to aid the readers in reproducing results and duplicating the prototype. While the system we built is not optimum for mass production, there will be sufficient technical specifications for anyone interested in such an endeavor.

2. System and prototype hardware

The wireless microphone system is based on the commercially available Audio-Technica Model number ATR288W. Wireless communications between the transmitter unit and the receiver unit are via 2 VHF channels: 169.505 MHz and 170.305 MHz. To improve performance, we purchased a Lavalier condenser microphone (Audio-Technica AT829MW) to replace the microphone that came with the unit. The microphone is coupled to the stethoscope, as shown in Figure 1, and connected to the transmitter which can be worn by the subject (Figure 1). The receiver's output is connected to the MICROPHONE input of the laptop. The maximum sampling rate of 44.1 kHz and amplitude resolution of 16 bit can be selected via software control. The PCG software determines the sampling rate according to the purpose of the run. The frequency response window from 35 kHz to 20 kHz is sufficiently wide for PCG waveforms. Low-pass filtering implemented in the software is used to control the upper frequency limit to 500 Hz. The ATR288W is compatible with both Macintosh: Mac OSX and Windows XP, Vista, 7 and 8 (USB 1 and 2). This compatibility allows the choice of any computer platforms from tablet to notebook size.

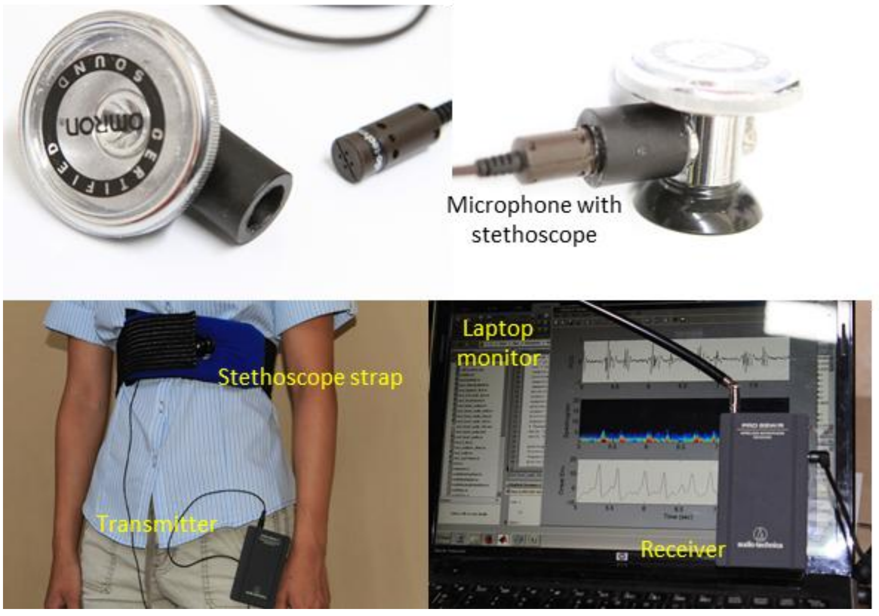

Fig.1 Off-the-shelf microphone and stethoscope (upper left). Side view of complete stethoscope head (upper right). The lower left panel shows the stethoscope strap and the lower right panel shows the laptop's screen and the microphone receiver unit.

A chest strap was made from a body icing kit purchased from CVS pharmacy. The kit was modified after the gel was removed. Polyester foam, sold for pillow stuffing, is inserted into the pad sleeve to shield the microphone from acoustic noise and provide a cushioned contact with the chest. A hole in the pad allows positioning the microphone in the middle of the pad and keeping it in contact with the chest (see Figure 1).

Any computer with a MICROPHONE input will work for this application. Our prototype is a notebook PC running Windows 7. While MATLAB computing language is not required in general, for rapid prototyping and easy leveraging of research algorithms available in the public domain, MATLAB R2013b, a scientific and engineering computing framework produced by Mathworks, is used to write the program. Figure 3 (upper panel) shows a typical PCG waveform.

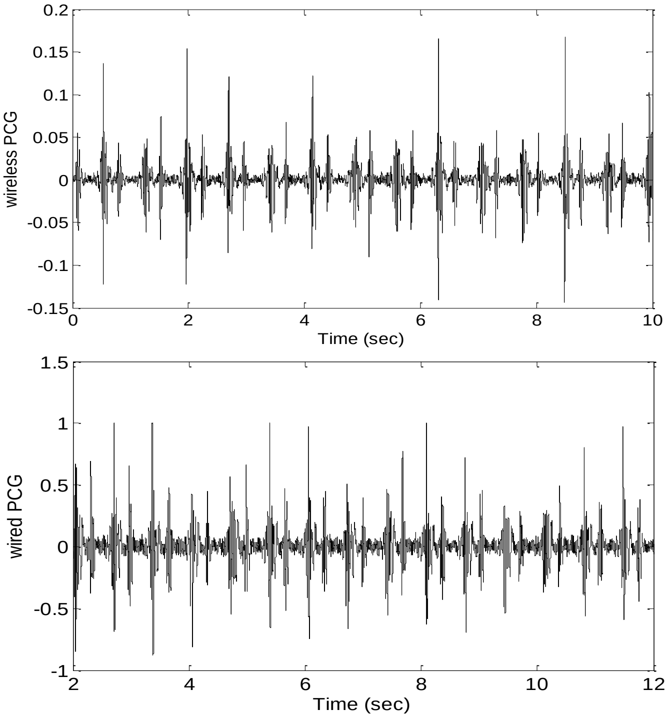

Fig. 2 A comparison of wired and wireless amplitudes shows that the voltage is lower in the case of the wireless but the signal-to-noise ratios (quality) are comparable. The difference in voltage amplitude is attributed to the fact that the wired microphone is USB-based and it has a dedicated amplifier.

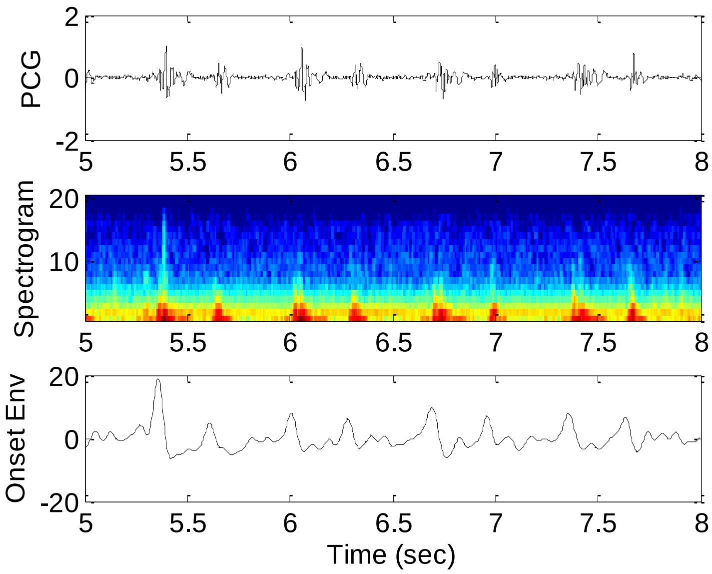

Fig. 3 PCG waveforms. Upper panel: 3 seconds of raw PCG record showing the voltage recorded by the PC on the vertical and time in seconds as the horizontal axis. Middle panel: Corresponding spectrogram. The horizontal axis shows time. The vertical axis shows increasing frequency bands (1 through 20) with the lowest frequency at the bottom. Color represents energy contained in each band (black =lowest and dark red=highest). The spectrogram indicates that PCG wave energy is concentrated in the low frequency bands as expected. Energy is also shown concentrated at the times of the heart sounds. Bottom panel: The onset strength envelope derived from the spectrogram. The *ose* reflects the total change in band energies and coincides with the onset of the "high energy" regions.

3. Segmentation techniques

The detection of the heart sounds S1 and S2 is accomplished with a beat finding technique developed for the music industry as discussed by Barabasa's paper [Barabasa, Jafari, & Plumbley, 2012] The specific beat tracking technique is based on dynamic programming [Davies & Plumbley, 2007]. In the first step of the detection algorithm, the audio signal is converted to the onset strength envelope (*ose*). The *ose* is calculated as the sum of the difference between the spectra of the current and previous waveform segments. The *ose* therefore represents the instantaneous overall change in spectral content (distribution of energy at different frequencies). To calculate the *ose*, a window of N data points is advanced in equal steps until the window reaches the end of the waveform. The number of data points N in each window

$$N \cong F_S/8 \quad (1)$$

corresponds to 1/8 second for the audio sampling frequency. The step is only half the size of the window so there is overlap between consecutive. The window is analyzed to calculate the spectral content or the energy contained in 20 frequency bins. The *ose* is calculated at each step *k* as

$$\Gamma(k) = \sum_{m=1}^{20} \left| S_m(k) - S_m(k-1) \right|^2 \tag{2}$$

The differences in power (S_m) in each of the 20 frequency bins between step k-1 and step k are squared and summed. The technique assumes that the *ose* correlates with the occurrence of a beat. As such, the likelihood of a beat is proportional to the magnitude of the change in spectral content and not in the amplitude of the waveform itself. Figure 3 shows the PCG waveform (upper panel), the spectrogram (middle), where the energy in each spectral band (frequency) is represented by color shading and the onset strength envelope (bottom panel) for the same time window. Note that the strength of the onset envelope is highest when the spectral contents begin to change. Other techniques of envelope extraction determine the beat as the time the waveform's amplitude or energy exceeds a threshold, hence locating the beat at a time later than the one predicted by the *ose*. The MATLAB script beat.m and all supporting functions are distributed as open source codes [Ellis, 2007] are incorporated in ours. The beat.m algorithm also encourages conformance to a global tempo which was pre-computed for the entire record. The use of both the *ose* and global tempo conformity improve the technique's robustness and immunity with respect to ambient noise.
The beat tracking algorithm can detect one of the two sequences of heart beats, S1 or S2. However, one cannot predict which one would be detected first. After the first sequence of beats is retrieved, its signature is dampened in the waveform and the algorithm is applied once more to retrieve the second sequence. The dampening of the signature of the first sequence in the waveform is accomplished by multiplying the waveform with a weighting function. The weighting function is unity everywhere but near zero where the beats were found in the first round. We find the following form quite effective:

$$W_i(x) = 1 - 0.8 \cdot \exp(-(x-\mu_i)^2 / 2\sigma^2), x = 1 \ldots D \tag{3}$$

where x is a location in the *ose*, D the length of the *ose*, is the position of the ith detected beat (in first sequence) and the width of the “ditches” in the weighting function. The weighting function is defined as one plus a series of inverse Gaussian functions. The latter are a series of ditches with small minima (<< 1) which, when multiplied to the original *ose*, would dampen the signature of the first sequence. The algorithm is applied once more to retrieve the second sequence. With both sequences retrieved, one still has to identify which one is S1. The codes identify the S1 sequence by inspecting the timing relationship between consecutive beats in the two sequences. Specifically, the separation between consecutive S1 beats cannot be greater than 1.3 times the average heart period and less than 0.22 seconds.

4. Data collection routine

Data collection first starts with strapping on the microphone over the heart, secondly wearing headphones to monitor and ensure the detection of heartbeats, and thirdly commanding the MATLAB program to record heart sounds and display its collection of PCG signal over a 50 second period. Longer records of 200 seconds are sometimes collected to study the heartbeat recovery phase after physical exercise. PCG were recorded only as a demonstration and not intended as a study of human subjects. The microphone is connected to the transmitter unit and the receiver is connected to the laptop to record microphonic sounds. A pair of headphones is also connected to another port in the laptop configured to monitor the audio from the microphone. Ideally, the microphone only detects the heart sounds of the chosen subject. Thus, data collection is best in a quiet room, the subject sits completely still, and the chest strap is adjusted so that the microphone is directly over the heart. However, the processing techniques are effective in alleviating the effects of extraneous noises. The individual can wear the wireless microphone, jog on a treadmill while data is collected. With the data taker listening through the headphones, he can help with the adjustment and placement of the sensor over the heart. Once the all the adjustments are made and collection is ready to be started, the data collector initiates the program to collect data.

5. Analyses and results

In a common data collect, 50 seconds of audio data is collected by the USB microphone by using the MATLAB *audiorecorder* built-in function, at a rate 32000 samples per second. The entire record consists of 1600000 numbers. The block diagram is shown in Figure 4 for reference. Since the sampling rate is much higher that the highest frequency found in the actual heart sound, high frequency signal higher than 1000 Hz is filtered out. The beat tracking script, beat.m, made available at the LabROSA internet site [Ellis, 2007] is designed to extract a single dominant beat. The codes are modified to extract both heart sounds by running the algorithm in two passes. After the first pass, the signal that corresponds to the first detected sequence of heart sounds is removed and the pruned signal is run again to detect the second sequence.

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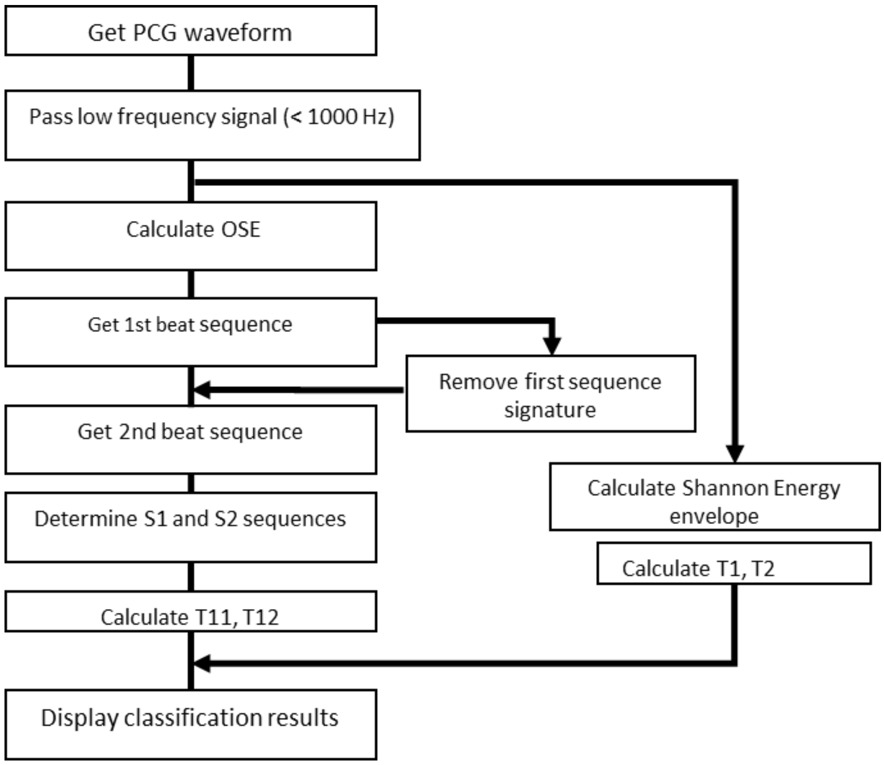

Fig. 4 Block diagram of PCG program

Using timing relationship between the S1 and S2 sounds, we determine which sequence is attributed to S1. The S1 and S2 beats are subsequently paired up and the beat intervals (T11) and the systolic intervals (T12) are computed. The additional diagnostic parameters, heart sound durations T1 and T2, are calculated directly from the Shannon energy envelope. The program displays the four diagnostic parameters and indicates the range of normal parameters. Users can use the display to classify the cardiac function for the targeted purpose.

6. Diagnostic parameters

The diagnostic parameters consist of the instants of the first heart sounds, S1 and S2 and parameters derived from them. It is conventional to define the characteristic times as in [Choi & Jiang 2005]. The interval T11 between consecutive S1 occurrences is defined as shown in Figure 5.

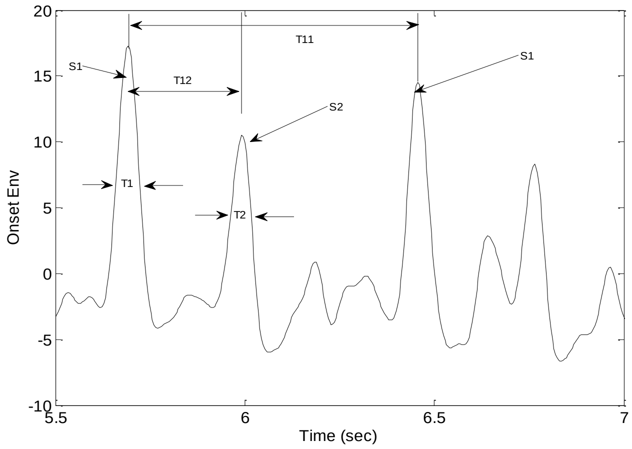

Fig. 5 Diagnostic parameters of the heart sounds. S1 and S2 are the instants of the first and second heart sound. T11 is the heart beat interval. T12 is the interval between the first and second heart sound.

While the recorded time of S1 depends on the technique of segmentation, the inter-beat interval is less affected by any bias on S1 itself. As remarked, the first sound instant retrieved by out segmentation technique is biased towards the onset of the generation of the sound as opposed to the time when the sound exceeds an artificially chosen threshold. Therefore, our S1 times are ahead of the ones chosen by other segmentation techniques. The systolic period (T12) is defined as the interval between S1 and S2. The diastolic period (T21=T11-T12) is the interval between S2 and the S1 of the following heartbeat. T12 and T21 are in principles not affected the mentioned bias. The relationship between the instantaneous heart rate (1/T11) and the systolic and diastolic periods, T12 and T21, were reported to be useful indicators for patients at rest, in exercise and taking medication [Bombardini et al., 2008]. For example, cardiac cycle anomalies of patients with heart conditions are characterized by an elongation of the systole and a shortening of the diastole. A reversal of the systolic/diastolic period ratio, e.g., going from less than 1 to above 1, may indicate a compromised cardiac function, e.g., a deficiency in cardiac filling. The systolic-diastolic change is accentuated during exercise but in the recovery, patients with heart conditions or on medication may show recovery trends different from a normal person. Figure 6 shows a scatter plot of T12 times (x 10) versus T11 times (x 10) for the participants in 50-second PCG records. Because the widths are only in the order of 0.01-0.03 seconds, an artificial magnification of 10 helps show the variability of T1 and T2 in the same scale as T12 and T11. The data points for each record are shown in different colors. The ellipse indicates the region where the [T12 ,T11] data point would fall for a normal person. Figure 6 also shows the scatter of the widths of the S1 and S2 sounds. The widths T1 and T2, defined as in Figure 4, are shown in Figure 6 for the mentioned PCG records.

To calculate the widths, we did not use the *ose* but used the Shannon energy envelope instead. The Shannon energy envelope is calculated as shown in Choi's paper [Choi & Jiang, 2008]. The square in the plot indicates the region where the [T1,T2] data points would be for a normal person. Because of the robustness of the segmentation technique with respect to varying heart rate, the system can monitor the heart sounds and perform reliably even when the heart rate is changing, such as in the recovery after physical exercise, e.g. slow walk on a treadmill. Figure 7 shows the recovery of the systolic/diastolic period ratio that follows the end of a treadmill jog. In this example, the ratio r, is shown for an

$$r = T12/(T11 - T12) \tag{4}$$

individual recovering from moderate exercise. The heart beat interval (T11) increases with elapsed time as shown in the left panel of Figure 7. The systolic period (T12) also decreases in the recovery. The systolic to diastolic period ratio, defined as in (4), is shown in the right panel of Figure 7. For this individual, the ratio is normal according to [Bombardini et al., 2008]. The reversal of the systolic/diastolic ratio, defined as a systole longer than the diastole, is capable of indicating abnormal condition induced by stress. In these measurements, we found the wireless USB microphone very convenient and the noise due to the walking not affecting the beat recording. Even when the interfering noise makes the algorithm miss a few beats, the general tempo was observed and the general trend of the characteristic times unaffected. The sensor can record the diagnostic parameters from the beginning of the exercise through the recovery phase.

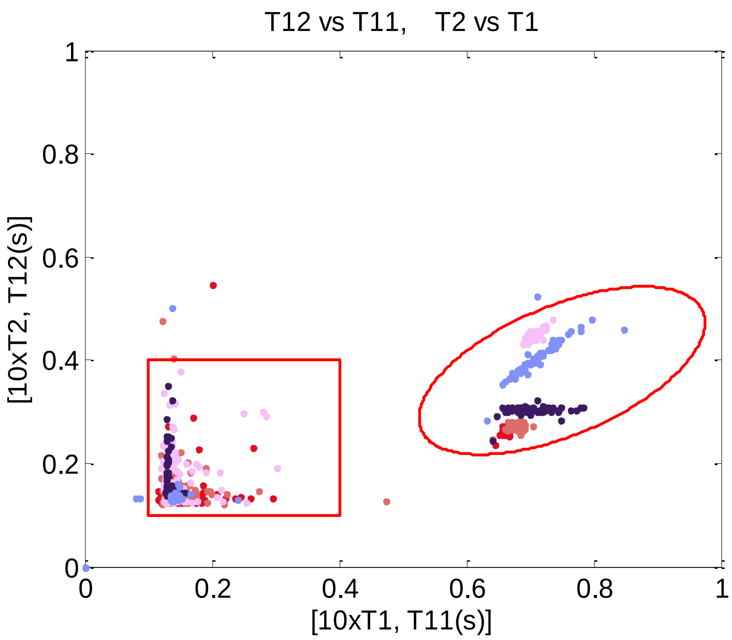

Fig. 6 Normal heart sound parameters.

7. Discussion and conclusion

The objective of demonstrating that a low-budget wireless PCG recorder and analyzer can achieve high performance with modern analysis techniques is met. An advanced segmentation technique, based on beat tracking algorithms developed for the music industry, relying on change in frequency contents instead of change in energy, has been instrumental in making the algorithm robust and immune to variation in background noise, heart sound volume and heart rate. Though the segmentation of the S1 and S2 sounds is achieved by detecting frequency content change, the width of the heart sounds is obtained with the Shannon energy envelope to be comparable with previously reported values. In the case of monitoring patients in or recovering from physical exercise, both the heart rate and sound volume correspond with the physical intensity. This situation requires a sensor and an analysis technique which is immune to the variability. The implemented technique is found to retrieve the heart sounds reliably under these strenuous conditions.

The sensor is a prototype system capable of producing sophisticated diagnostic parameters. The first and second heart sounds, as well as the additional diagnostic parameters T1, T2, T11, and T12 could be recorded reliably and displayed in plots that convey pathological information about the cardiac cycle. The diagnostic tool can be useful in many scenarios: patients needing long term and persistent monitoring in a home care setting with or without the assistance of care providers, primary care physicians, physical therapists, or students needing an affordable educational tool. We would like to extend the study to include anomalous and pathological heart sounds in the next phase of our research.

Acknowledgment

The faculty in the Chemistry Department of Amherst College has been instrumental in this project and extremely helpful with their advice and encouragement. We benefited from the Lab for Recognition and Organization of Speech and Audio -coversongID software which was generously distributed by Professor Dan Ellis, University of Columbia.

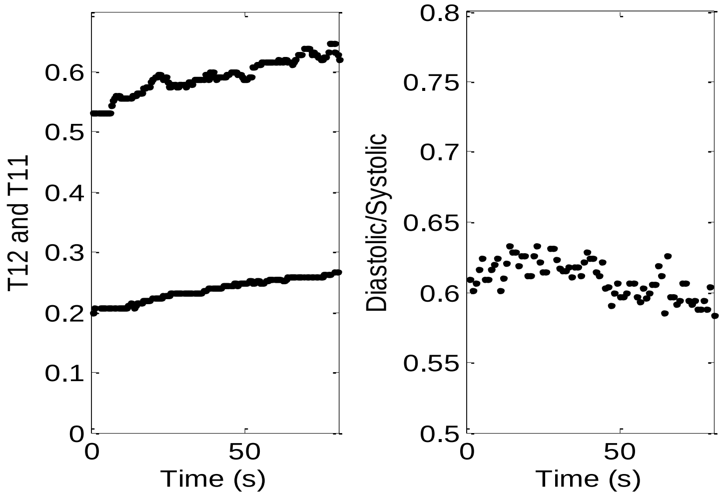

Fig. 7 Diagnostic parameters derived from the PCG recorded in the recovery from exercise.

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