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Comparing on Sparse Heart Sound Recovery Algorithms

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Abstract— **This paper applied the concept of Compressive Sensing on practical problem for sparse heart sound recovery. The sparse representation matrix used Haar wavelet transform, while the measurement matrix used random orthogonal matrix. We compare the performance of different recovery algorithm such as Subspace Pursuit (SP), Iterative Hard Thresholding (IHT), Compressive Sampling Matching Pursuit(CoSaMP), Orthogonal Matching Pursuit (OMP), and L1 norm optimization. The experiment results show that all of method can recovery a periodic heart beat sound. The best recovery performance is L1 norm, but the computational time is worse.**

Keywords: ***Sparse; Heart Sounds; Recovery; Compressive Sensing***

I. INTRODUCTION

Cardiovascular disease (CVD) is prevalent remains the leading cause of death worldwide. One of the first steps in evaluating the cardiovascular system is the heart sounds examination. Auscultation of the heart record is monitoring activity of the heart and fortunately used as early detection of the cardiovascular diseases. Some of the mechanisms of heart sounds are generated include opening or closure of the heart valves, flow of blood through the valve, flow of blood into the ventricular chambers, and rubbing of cardiac surfaces. The heart sounds can be used as an indication to diagnose a non-invasive of the cardiac failures [1].

However, monitoring of heart sounds needs compelled on data processing and acquisition. To admittance these issues compressive sensing (CS) is used, CS that compressed data acquisition protocols which can do acquire directly just the important of the signals information. It support to decrease the steps number include when combining sampling data and compression become only one step [2, 3].

Compressed Sensing (CS) [4, 5, 6, 7, 8] seeks to represent real, especial audio signals there are no-spare, and its is analyzed the stability of signals in a short-term. The Nyquist rate is used for signal sampling. The measurements of sampling number is lower than the number of samples needed. Signals that compressed using compressed sensing method have interest to reduced space of storage and transmission bandwidth because of the activity compression achieved. Experiment compare the performance of different recovery algorithm such as Subspace Pursuit (SP), Iterative Hard Thresholding (IHT), Compressive Sampling Matching Pursuit (CoSaMP), Orthogonal Matching Pursuit (OMP), and L1 norm optimization and the experiment show the measurements rate and window size of the frames are related to the performance of reconstruction .

II. COMPRESSED SENSING

Heart sounds signals have exclusive stability of short-term. Characteristics of heart sounds signals contain of the time-varying, a non-stationary for some special audio signals on stochastic process. Usually in reconstruction, there are not sparse and many non-zero components [9]. The characteristics of audio signals are dynamic in time, however the signals were stable in a short time, short-term stability could be compressed with method of compressed sensing. At the last for a long time, signals were being divided and analyzed and into several signals with short-time duration, a frame is named for the short-time signal, that usually length is 7~15s. Recovery and reconstituted an audio signal with complete approximate are used mathematical algorithm to make the exact and simultaneous reconstructed. Signal after compressed with CS method in every frame with algorithm like Subspace Pursuit (SP), Iterative Hard Thresholding (IHT), Compressive Sampling Matching Pursuit (CoSaMP), Orthogonal Matching Pursuit (OMP), and L1 norm optimization. Compressed Sensing in audio signals is shown in fig.1. Process of reconstruction can be used for solving an optimization problem.

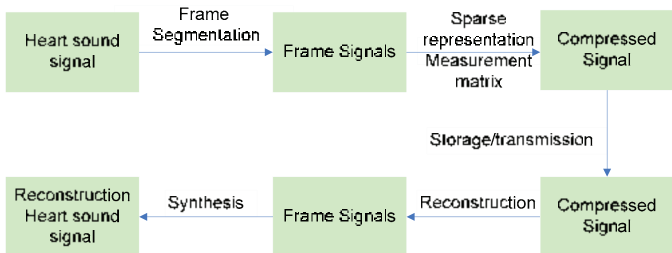

Fig.1.Heart sound signal processing based on compressive sensing

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How accurately the heart sounds from suitability of compressive sensing can be examined, by sparse samples recovering using the Mean Square Error (MSE) and Signal to Noise Ratio (SNR) [11]. Effectiveness of compressive sensing is evaluated through performance metrics as seen below that commonly used in biomedical applications [12,13].

- MSE is used as a standard statistical metric to measure performance of a model to find the optimal approximation. Its measures distortion and defined as:

$$MSE = \frac{\sum_{n=1}^{N}\left(x(n)-\hat{x}(n)\right)^2}{N} \quad (1)$$

- The leverage reconstruction signal to noise ratio is measure in dB, SNR is defined as:

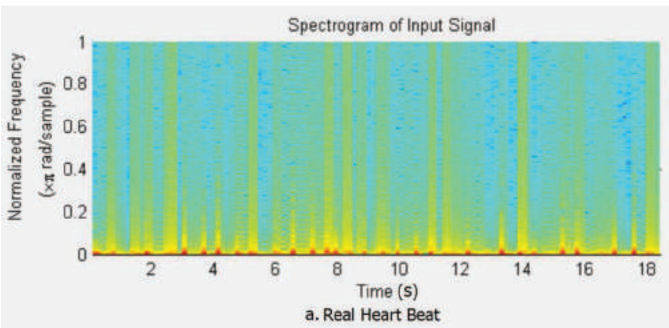
$$SNR\ (x, \hat{x}) = 10 \log 10 \left(\frac{\|x\|_2^2}{\|x-\hat{x}^*\|_2^2}\right) \quad (2)$$

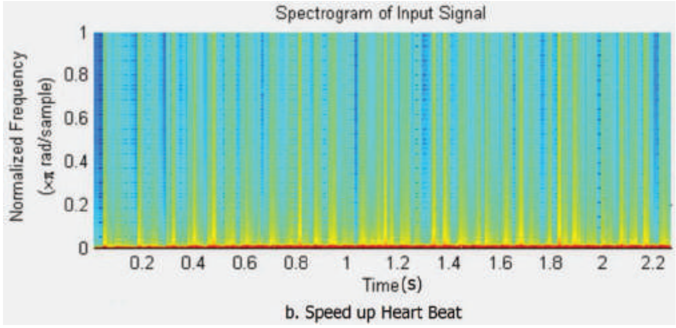
III. Discussion

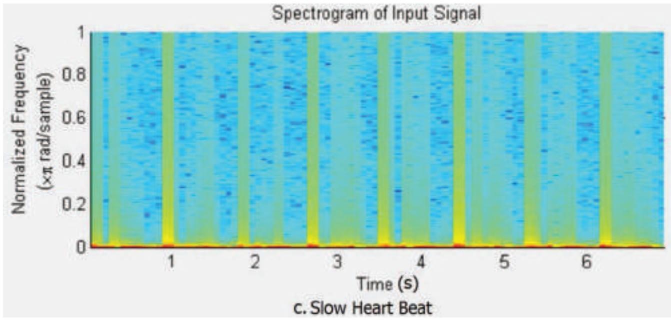
Our system describe in Fig.1, for compressive sensing of sparse heart sound signal. The input signal is represented by haar wavelet transform to get sparse from the real signal [14]. As for the measurement matrix is used random orthogonal [15,16]. This paper compare 5 method for recovery heart sound, such us Subspace Pursuit (SP) [17,18], Iterative Hard Thresholding (IHT) [19], Compressive Sampling Matching Pursuit (CoSaMP) [20], Orthogonal Matching Pursuit (OMP) [21], and L1 norm optimization [22]. We use 4 example of heart sound shown in table 1. The spectrogram of input signals are shown in figure 2.

TABLE I. HEART SOUNDS DATA

Name of Signal	Frequency of Sampling (sample/second)	Duration (s)
Real Heart Beat	96,000	12.14310
Speed up Heart Beat	48,000	29.76730
Slow Heart Beat	44,100	9.95694
Heart rate monitor	44,100	13.70800







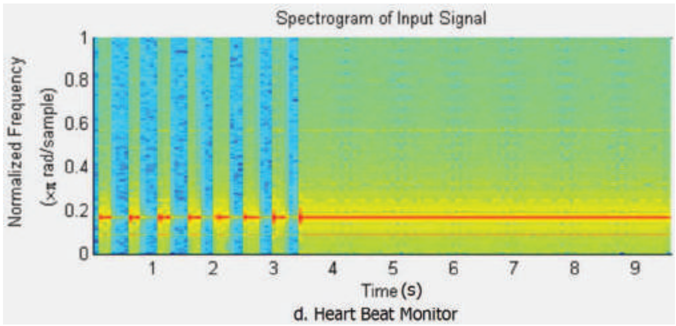


Fig. 2. Spectrogram of input signals: a. Real Heart Beat, b. Speed up Heart Beat, c. Slow Heart Beat, d. Heart Rate Monitor.

IV. Experiment Results And Analysis

This section describes some experiment to explore the performance and computational time process for different algorithm. Fig. 3 shows the processing of sparse heart sound recovery using compressive sensing. The input signal is real heartbeat.wav that showed in Fig.3.a. The signal is processed in 12.14310s using dictionary composed by 512 windowed sinusoid. The signal is sampled at 96 KHz. And we assume the sparsity of K=10%. In figure 3.b, the measured signal is shown. This process used L1 norm optimization, while the result of all reconstruction algorithm can be seen in figure 4. It can be analyzed that CS can recovery a periodic signal such as heart beat, although some of the upper part of the spectrum have been lost. And L1 norm reconstruction results closest to the input signal compared to the other algorithm.

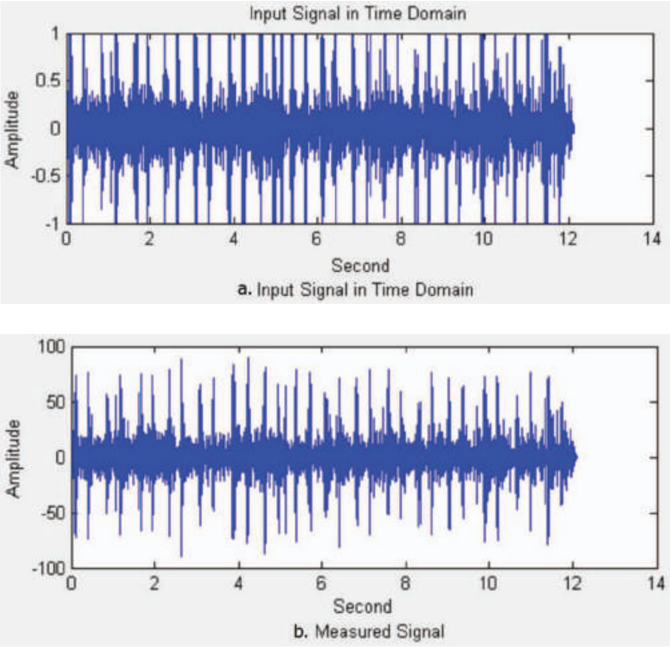
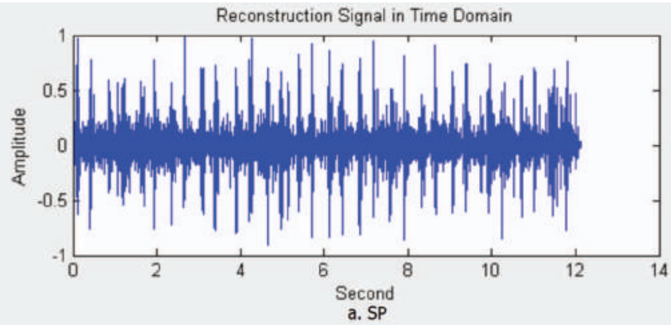
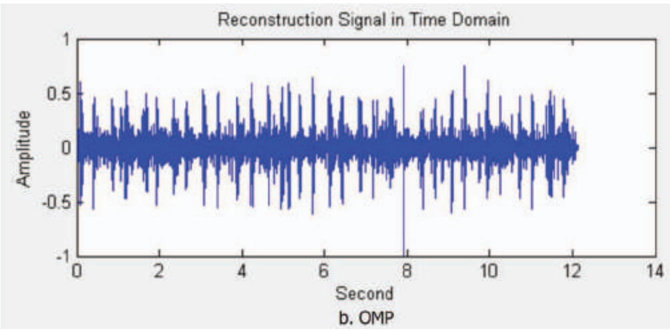
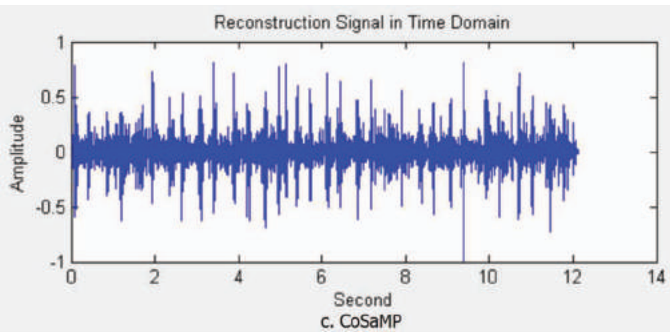
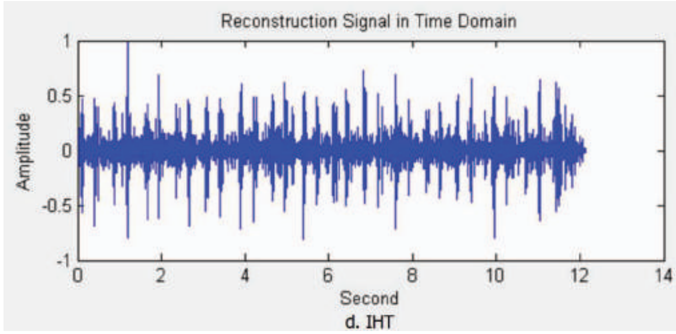


Fig. 3. Signal Processing: a. Input Signal, b. Measured Signal.









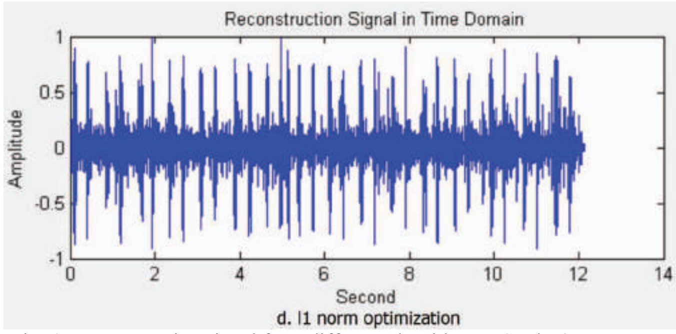


Fig. 4. Reconstruction signal from different algorithm: a. SP, b. OMP, CoSaMP, d. IHT, e. L1 norm

Figure 5 showed the relationship between mean square error and the number of sparse signal. The larger of sparsity rate will increase mean square error. It indicates that the improvement in recovery quality depend on the number of sparse rate decreased. L1 norm optimization has the best performance than the other method.

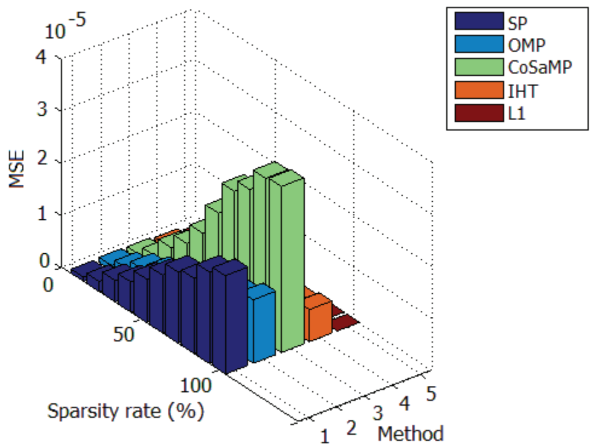


Fig. 5. The effect of the sparsity samples to mean square error (MSE)

The relationship between the window size of frame and the signal to noise ratio (SNR) of different recovery algorithms is shown in table 2. The simulation used the real heart beat data and the rate of measurement is 50%. The length of windows is 512, 1024, and 2048. It can be indicate that the larger size of the window frame, the better its performance recovery.

TABLE II. SNR VALUES FOR THE FRAME WINDOW

Method	SNR for w=512 (dB)	SNR for w=1024 (dB)	SNR for w=2048 (dB)
SP	1.88	6.06	8.19
OMP	1.96	6.12	9.88
CoSaMP	1.48	5.88	8.96
IHT	2.22	6.78	9.67
L1 Norm	4.14	8.32	11.41

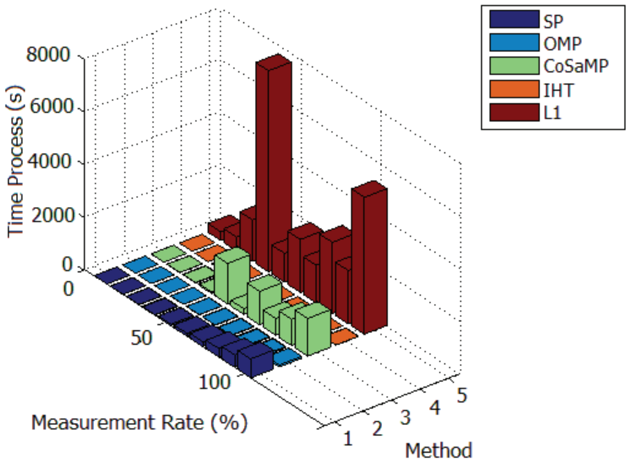


Fig. 6. Time process (s) and measurement rate (%) trade off. It is good practice to explain the significance of computational process.

We observed computational time comparison for all algorithm that shown in Figure 6. It can conclude that the increment of measurement rate will affect the increment of computational time. The OMP method is the fastest algorithm.

We use Mean Opinion Score (MOS) to assesssubjectively the audio quality [23, 24]. MOS testing is done by taking a sampling of the 20 respondents who listen to the audio quality by comparing the input signal and the reconstructed signal. They judge the quality by selecting a score that is set as follows: 5=excellent, 4=good, 3=fair, 2=poor, 1=bad. The results of an average MOS testing is shown in figure 7. The average MOS of L1-norm is highest than the other method. The score is more than 3.5 for all heart beat data, it means that the quality of audio signal reconstruction is good.

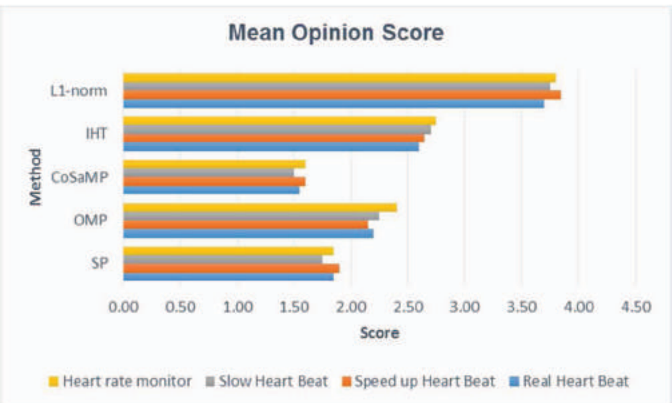


Fig. 7. Mean opinion score from different reconstruction algorithms that tested to all heart beat data

V. CONCLUSION AND FUTURE WORK

We have applied the concept of Compressive sensing on practical problem for sparse heart sound recovery. The experimental results show that compressive sensing can recover a periodic heart beat signal. The recovery performance depends on the measurements rate and the window size of frames. L1 norm optimization method has the best performance for recovering signal but the computational time is worse than the others. Based on a subjective test results using MOS, L1 norm has the highest score compared to the other algorithms, ie more than 3.5. It indicates that the quality of the reconstructed audio signal is good and can be used to analyze heart disease. The challenge is an important observation as the accuracy of the algorithm for less computational time.

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