Recovering heart sounds from sparse samples

Ervin Sejdić and Luis F. Chaparro

Department of Electrical and Computer Engineering, University of Pittsburgh, Pittsburgh, PA, USA
E-mails: esejdic@ieee.org

ABSTRACT

Continuous monitoring of physiological functions such as heart sounds can pose severe constraints on data acquisition and processing systems, especially if remote monitoring is desired. In this paper, we investigate the utility of a recently proposed compressive sensing (CS) algorithm based on modulated discrete prolate spheroidal sequences (MDPSS) for recovering sparsely sampled heart sounds. In particular, we investigate the recordings containing opening snap (OS) or the third heart sounds (S3) in addition to first and second heart sounds. The results of numerical analysis show that heart sounds can be accurately reconstructed even when the sampling rate is reduced to 40% of the original sampling frequency.

Index Terms— Compressive sensing, heart sounds.

1. INTRODUCTION

Cardiovascular disease remains the leading cause of death worldwide despite numerous advances in monitoring and early detection of the diseases. Fortunately, clinical experience has shown that heart sounds can be an effective tool to noninvasively diagnose some of the heart failures [1], since they provide clinicians with valuable diagnostic and prognostic information concerning the heart valves and hemodynamics. Heart auscultation is an important technique allowing the detection of abnormal heart behaviour before it can be detected using other techniques such as the ECG [2].

However, continuous monitoring of heart sounds poses severe constraints on data acquisition and processing systems in telemedicine. One approach to alleviate these issues is compressive sensing (CS) that advocates to diminish the number of steps involved when acquiring data by combining sampling and compression into a single step [3], [4], [5].

In this paper, we examine the suitability of a recently proposed CS approach for heart sounds. The CS approach is based on MDPSS [6]. Using the CS approach, we carried out a numerical analysis of heart sounds which showed that we can obtain 90% cross-correlation between the reconstructed signals and the actual signals using only 40% percent of samples. This has been observed for recordings containing either OS or S3.

2. DATA ANALYSIS

2.1. Data

Phonocardiograph recordings of actual heart sounds containing either opening snap (OS) or the third heart sound (S3) in addition to first and second heart sounds were obtained from patients at St. Joseph's Hospital in Toronto, Canada during clinical examinations that also included heart auscultation. The data acquisition system consisted of a PC fitted with a 16-bit acquisition board and of an analog recorder/player (Cambridge AVR-I). The heart sounds are sampled at 4000 Hz for 4096 samples (1.024 seconds in length) [7].

2.2. Reconstruction of compressively sampled heart sounds

To examine the suitability of compressive sensing for heart sounds, we consider how accurately heart sounds can be recovered from sparse samples using the recently proposed approach [6]. To examine the accuracy we consider two different scenarios where a different number of samples is available. First, we only consider when 40% of the original samples is available. Secondly, 60% of the original samples are used to examine the recovery accuracy. For both cases, the effects of the uniform or non-uniform sub-Nyquist sampling are examined. In this numerical experiment, we use a 10-band MDPSS based dictionary with the normalized half-bandwidth equal to 0.25. The effectiveness of compressive sensing of heart sounds is evaluated through performance metrics used in other biomedical applications (e.g., [5]):

- Cross-correlation (γ) is used to evaluate the similarity between the original and the reconstructed signal, and is defined as:

$$\gamma = \frac{\sum_{n=1}^{N}\left(x(n)-\mu_x\right)\left(\widehat{x}(n)-\mu_{\widehat{x}}\right)}{\sqrt{\sum_{n=1}^{N}\left(x(n)-\mu_x\right)^2}\sqrt{\sum_{n=1}^{N}\left(\widehat{x}(n)-\mu_{\widehat{x}}\right)^2}}\times 100\% \tag{1}$$

  where $x(n)$ is the original signal and $\widehat{x}(n)$ represents a reconstructed signal. In addition, μ_x and $\mu_{\widehat{x}}$ denote the mean values of $x(n)$ and $\widehat{x}(n)$, respectively.

- The percent root difference (ρ) defined as:

$$\rho(\%) = \sqrt{\frac{\sum_{n=1}^{N}\left(x(n)-\widehat{x}(n)\right)^2}{\sum_{n=1}^{N}x^2(n)}}\times 100\% \tag{2}$$

  measures distortion in reconstructed biomedical signals.

- The root mean square error (ε) measures distortion and is often beneficial to minimize this metric when finding the optimal approximation of the signal. RMSE is defined as:

$$\varepsilon = \sqrt{\frac{\sum_{n=1}^{N}\left(x(n)-\widehat{x}(n)\right)^2}{N}} \tag{3}$$

- The maximum error (ξ) denotes the largest error between the samples of the original signal and the reconstructed signal:

$$\xi = \max\left(x(n)-\widehat{x}(n)\right) \tag{4}$$

3. RESULTS

Sample signals are shown in Figure 1, while Tables 1 and 2 show the results of the numerical analysis when the proposed scheme is applied to heart sounds.

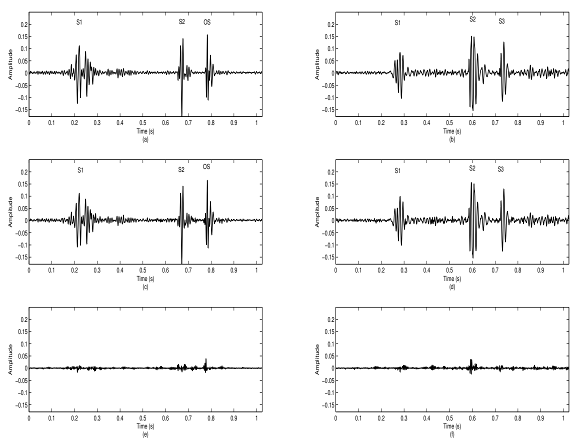

Fig. 1. Sample heart sounds from patients: (a) the original signal containing the OS; (b) the original signal containing the S3; (c) the recovered signal containing the OS (40% samples, $\gamma = 98.9\%$); (d) the recovered signal containing the S3 (40% samples, $\gamma = 99.0\%$); (e) the error between the original and the recovered signal with the OS; (f) the error between the original and the recovered signal with the OS.

The results show that we can very accurately reconstruct the heart sounds from the sparsely sampled recordings. As expected, more accurate results were achieved with 60% of samples than with 40% of samples when considering the cross-correlations (γ) results.

Table 1. Accuracy for recovery of heart sounds while using 40% of samples.

	Uniform		Random	
	OS	S3	OS	S3
γ	96.2 ± 3.50	95.9 ± 2.99	83.4 ± 6.37	83.5 ± 4.48
ρ	25.3 ± 9.83	27.3 ± 8.95	25.3 ± 9.82	27.3 ± 12.4
ε	0.01 ± 0.01	0.01 ± 0.00	0.01 ± 0.01	0.01 ± 0.01
ξ	0.04 ± 0.02	0.03 ± 0.02	0.10 ± 0.07	0.09 ± 0.06

Less accurate results have been obtained when using non-uniform (random) sampling times in comparison to uniform sampling for both 40% of samples and 60% of samples. These results follow the previously reported trends which show that it is more challenging to recover the signal accurately with non-uniform samples. However, as we use a larger number of samples (e.g., 60% of samples), the original signals can be recovered very accurately from randomly sparse samples. Specifically, the results obtained with 60% of samples with non-uniform sampling are comparable to the results obtained with 40% of samples when using uniform sampling.

The results also show that the considered CS approach is an accurate reconstruction method regardless of the present heart sounds. Specifically, we considered recordings containing OS or S3 in addition to first and second heart sounds. The presented results showed

Table 2. Accuracy for recovery of heart sounds while using 60% of samples.

	Uniform		Random	
	OS	S3	OS	S3
γ	99.6 ± 0.40	99.6 ± 0.20	94.6 ± 4.39	95.6 ± 1.09
ρ	8.63 ± 4.25	8.43 ± 1.80	30.6 ± 10.7	27.3 ± 4.06
ε	0.01 ± 0.00	0.01 ± 0.00	0.01 ± 0.01	0.01 ± 0.01
ξ	0.02 ± 0.01	0.01 ± 0.01	0.06 ± 0.04	0.04 ± 0.02

that CS approach based on MDPSS is robust to changes in the underlying physiological process, which is a desirable property from a systems point of view. This inherently implies that any future systems developed for sparse sampling of heart sounds can use a uniform sampling scheme regardless of the present physiological phenomena.

Therefore, based on the presented results, we can state with high confidence that CS based on the time-frequency dictionary containing MDPSS is suitable scheme for heart sounds. Particularly accurate results have been obtained when we use 60% of samples. We expect that further improvements can be achieved by optimizing the parameters of the recovery process with respect to the considered error metrics.

4. CONCLUSIONS

In this paper, we examined the suitability of a recently proposed compressive sensing algorithm for accurate reconstruction of heart sounds from sparse samples. The CS algorithm was tested using recordings containing OS or S3 in addition to the first and second heart sounds. The results of numerical analysis showed that the considered CS approach to be suitable for these recordings. Specifically, we achieved very accurate representations of these signals even when the heart sounds were subsampled at by 60% below the original sampling frequency.

5. REFERENCES

[1] L. Durand and P. Pibarot, "Digital signal processing of the phonocardiogram: Review of the most recent advancements," *Critical Reviews in Biomedical Engineering*, vol. 23, no. 3-4, pp. 169–219, 1995.

[2] M. Obadiat, "Phonocardiogram signal analysis: Techniques and performance analysis," *Journal of Medical Engineering and Technology*, vol. 17, no. 6, pp. 221–227, Nov./Dec. 1993.

[3] D. L. Donoho, "Compressed sensing," *IEEE Transactions on Information Theory*, vol. 52, no. 4, pp. 1289–1306, Apr. 2006.

[4] S. Senay, L. F. Chaparro, and L. Durak, "Reconstruction of nonuniformly sampled time-limited signals using prolate spheroidal wave functions," *Signal Processing*, vol. 89, no. 12, pp. 2585–2595, Dec. 2009.

[5] K.-K. Poh and P. Marziliano, "Compressive sampling of EEG signals with finite rate of innovation," *EURASIP Journal on Advances in Signal Processing*, vol. 2010, p. 12 pages, 2010, article ID 183105.

[6] E. Sejdić, A. Can, L. F. Chaparro, C. M. Steele, and T. Chau, "Compressive sampling of swallowing accelerometry signals using time-frequency dictionaries based on modulated discrete prolate spheroidal sequences," *EURASIP Journal on Advances in Signal Processing*, 2012, submitted.

[7] E. Sejdić and J. Jiang, "Selective regional correlation for pattern recognition," *IEEE Transactions on Systems, Man and Cybernetics - Part A*, vol. 37, no. 1, pp. 82–93, Jan. 2007.