Classification of Seismocardiographic Cycles into Lung Volume Phases

Brian E. Solar, Amirtaha Taebi, Hansen A. Mansy
Biomedical Acoustics Research Laboratory, University of Central Florida, Orlando, FL 32816, USA
{bsolar@knights., taebi@knights., hansen.mansy@} ucf.edu

In this study, a machine learning algorithm was developed to classify seismocardiographic (SCG) signals occurring during low and high lung volumes. The results demonstrated that morphological differences can be observed in SCG waveforms during respiration. SCG events were classified using a Radial Basis Function (RBF) support vector machine (SVM) algorithm into the two classes of low and high lung volume. Classification accuracy was found to be about 75%.

Measurements of vibrations from the chest surface due to the heart activity are called seismocardiographic (SCG) signals [1]–[4]. SCG signal morphology can be affected by respiration since it triggers known changes in physiological parameters (such as intrathoracic pressure, stroke volume, etc.) [5], [6]. SCG events occurring during low and high lung volume (LLV and HLV, respectively) may have different characteristics [7], [8]. Accurate classification of SCG events into LLV and HLV groups might lead to a more accurate estimation of SCG signal feature points, enhance our understanding of SCG genesis, and help explain SCG changes with cardiac pathology. For the first time, in this study, SCG events during LLV and HLV were classified using a machine learning algorithm.

Eight healthy individuals enrolled in the study after informed consent. Respiratory flow rate and SCG were measured simultaneously. A triaxial accelerometer (356A32, PCB Piezotronics, Depew, NY) was used to capture the SCG signals. The sensor was placed at the left lower sternal border and the level of the 4^{th} intercostal space using a double-sided tape. The lung volume signal was calculated as the integral of respiratory flow rate. The SCG events were then grouped into either LLV or HLV using the lung volume signal. A support vector machine (SVM) with a RBF Kernel was trained on the SCG events classified as occurring during LLV or HLV. 710 samples (i.e., SCG events) were used to train, and 178 were used as testing (i.e., 80/20 train and test split). There was an equal number of LLV and HLV events. Three SVM models were trained; SCG1, SCG2 (occurring around the first and second heart sounds, respectively), and SCG (the total cardiac cycle). 14 spectral features (sample entropy, spectral entropy, median, skewness, Kolmogorov complexity, etc.) were extracted. These features were selected by reviewing relevant literature [9]. The extracted features were used as the inputs for the SVM and the occurrence of LLV or HLV were the outputs. Matlab (R2015b, The MathWorks, Inc, Natick, MA) was used to preprocess the signals. The machine learning analysis was implemented with Python Scikit-Learn.

The RBF SVM was used to classify the SCG events into LLV and HLV classes. For SCG, SCG1, and SCG2 the accuracies were 75%, 77%, and 75%, respectively. The identification accuracy for all three SVM models were also obtained using K-fold cross-validation method ($k = 20$). For SCG, SCG1, and SCG2 models and the accuracies were 73%, 74%, and 75%, respectively. These results suggest that SVM might be used to classify SCG events into LLV and HLV classes. The main limitation of this study was the relatively low number of samples which may have reduced accuracies.

The results of this study showed that the SCG demonstrated morphological differences during respiration. SCG events were classified using a RBF SVM algorithm into the two classes of LLV and HLV. Classification accuracy was found to be about 75%. Studying the effect of respiration allows separating SCG into groups with similar events. This reduces SCG waveform variability and enables more precise estimation of SCG characteristics. Future studies may focus on using different machine learning approaches including unsupervised learning techniques to cluster similar SCG events.

Research reported in this publication was supported by the National Institutes of Health under R44HL099053.

References

[1] A. Taebi and H. A. Mansy, “Time-frequency Analysis of Vibrocardiographic Signals,” in *2015 BMES Annual Meeting*, 2015.

[2] A. Taebi and H. A. Mansy, “Time-frequency Description of Vibrocardiographic Signals,” in *38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2016.

[3] A. Taebi and H. A. Mansy, “Effect of Noise on Time-frequency Analysis of Vibrocardiographic Signals,” *J. Bioeng. Biomed. Sci.*, vol. 6(202), p. 2, 2016.

[4] A. Taebi and H. A. Mansy, “Analysis of Seismocardiographic Signals Using Polynomial Chirplet Transform and Smoothed Pseudo Wigner-Ville Distribution,” in *Signal Processing in Medicine and Biology Symposium (SPMB), 2017 IEEE*, 2017, pp. 1–6.

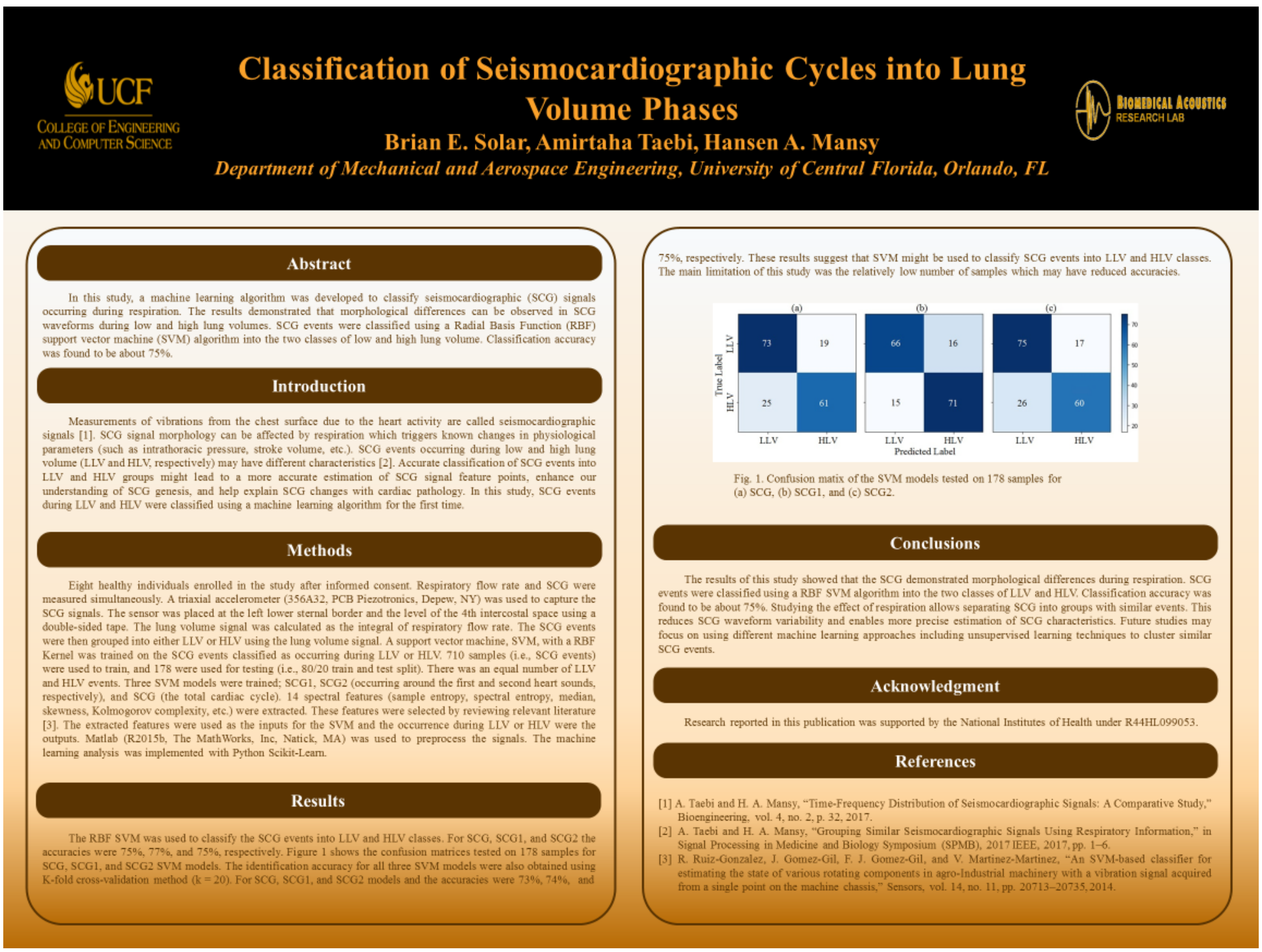
[5] A. Taebi and H. A. Mansy, “Time-Frequency Distribution of Seismocardiographic Signals: A Comparative Study,” *Bioengineering*, vol. 4, no. 2, p. 32, 2017.

[6] A. Taebi and H. A. Mansy, “Noise Cancellation from Vibrocardiographic Signals Based on the Ensemble Empirical Mode Decomposition,” *J. Biotechnol. Bioeng.*, vol. 2, no. 2, p. 00024, 2017.

[7] A. Taebi and H. A. Mansy, “Grouping Similar Seismocardiographic Signals Using Respiratory Information,” in *Signal Processing in Medicine and Biology Symposium (SPMB), 2017 IEEE*, 2017, pp. 1–6.

[8] A. Taebi, R. H. Sandler, B. Kakavand, and H. A. Mansy, “Seismocardiographic Signal Timing with Myocardial Strain,” in *Signal Processing in Medicine and Biology Symposium (SPMB), 2017 IEEE*, 2017, pp. 1–2.

[9] R. Ruiz-Gonzalez, J. Gomez-Gil, F. J. Gomez-Gil, and V. Martinez-Martinez, “An SVM-based classifier for estimating the state of various rotating components in agro-Industrial machinery with a vibration signal acquired from a single point on the machine chassis,” *Sensors*, vol. 14, no. 11, pp. 20713–20735, 2014.



Classification of Seismocardiographic Cycles into Lung Volume Phases

Brian E. Solar, Amirtaha Taebi, Hansen A. Mansy

Department of Mechanical and Aerospace Engineering, University of Central Florida, Orlando, FL

UCF College of Engineering and Computer Science

Biomedical Acoustics Research Lab

Abstract

In this study, a machine learning algorithm was developed to classify seismocardiographic (SCG) signals occurring during respiration. The results demonstrated that morphological differences can be observed in SCG waveforms during low and high lung volumes. SCG events were classified using a Radial Basis Function (RBF) support vector machine (SVM) algorithm into the two classes of low and high lung volume. Classification accuracy was found to be about 75%.

Introduction

Measurements of vibrations from the chest surface due to the heart activity are called seismocardiographic signals [1]. SCG signal morphology can be affected by respiration which triggers known changes in physiological parameters (such as intrathoracic pressure, stroke volume, etc.). SCG events occurring during low and high lung volume (LLV and HLV, respectively) may have different characteristics [2]. Accurate classification of SCG events into LLV and HLV groups might lead to a more accurate estimation of SCG signal feature points, enhance our understanding of SCG genesis, and help explain SCG changes with cardiac pathology. In this study, SCG events during LLV and HLV were classified using a machine learning algorithm for the first time.

Methods

Eight healthy individuals enrolled in the study after informed consent. Respiratory flow rate and SCG were measured simultaneously. A triaxial accelerometer (356A32, PCB Piezotronics, Depew, NY) was used to capture the SCG signals. The sensor was placed at the left lower sternal border and the level of the 4th intercostal space using a double-sided tape. The lung volume signal was calculated as the integral of respiratory flow rate. The SCG events were then grouped into either LLV or HLV using the lung volume signal. A support vector machine, SVM, with a RBF Kernel was trained on the SCG events classified as occurring during LLV or HLV. 710 samples (i.e., SCG events) were used to train, and 178 were used for testing (i.e., 80/20 train and test split). There was an equal number of LLV and HLV events. Three SVM models were trained; SCG1, SCG2 (occurring around the first and second heart sounds, respectively), and SCG (the total cardiac cycle). 14 spectral features (sample entropy, spectral entropy, median, skewness, Kolmogorov complexity, etc.) were extracted. These features were selected by reviewing relevant literature [3]. The extracted features were used as the inputs for the SVM and the occurrence during LLV or HLV were the outputs. Matlab (R2015b, The MathWorks, Inc, Natick, MA) was used to preprocess the signals. The machine learning analysis was implemented with Python Scikit-Learn.

Results

The RBF SVM was used to classify the SCG events into LLV and HLV classes. For SCG, SCG1, and SCG2 the accuracies were 75%, 77%, and 75%, respectively. Figure 1 shows the confusion matrices tested on 178 samples for SCG, SCG1, and SCG2 SVM models. The identification accuracy for all three SVM models were also obtained using K-fold cross-validation method (k = 20). For SCG, SCG1, and SCG2 models and the accuracies were 73%, 74%, and 75%, respectively. These results suggest that SVM might be used to classify SCG events into LLV and HLV classes. The main limitation of this study was the relatively low number of samples which may have reduced accuracies.

Fig. 1. Confusion matix of the SVM models tested on 178 samples for (a) SCG, (b) SCG1, and (c) SCG2.

Conclusions

The results of this study showed that the SCG demonstrated morphological differences during respiration. SCG events were classified using a RBF SVM algorithm into the two classes of LLV and HLV. Classification accuracy was found to be about 75%. Studying the effect of respiration allows separating SCG into groups with similar events. This reduces SCG waveform variability and enables more precise estimation of SCG characteristics. Future studies may focus on using different machine learning approaches including unsupervised learning techniques to cluster similar SCG events.

Acknowledgment

Research reported in this publication was supported by the National Institutes of Health under R44HL099053.

References

[1] A. Taebi and H. A. Mansy, “Time-Frequency Distribution of Seismocardiographic Signals: A Comparative Study,” Bioengineering, vol. 4, no. 2, p. 32, 2017.

[2] A. Taebi and H. A. Mansy, “Grouping Similar Seismocardiographic Signals Using Respiratory Information,” in Signal Processing in Medicine and Biology Symposium (SPMB), 2017 IEEE, 2017, pp. 1–6.

[3] R. Ruiz-Gonzalez, J. Gomez-Gil, F. J. Gomez-Gil, and V. Martinez-Martinez, “An SVM-based classifier for estimating the state of various rotating components in agro-Industrial machinery with a vibration signal acquired from a single point on the machine chassis,” Sensors, vol. 14, no. 11, pp. 20713–20735, 2014.