Determining the respiratory state from a seismocardiographic signal - A machine learning approach

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Abstract

Seismocardiography (SCG) is the measurement of vibrations on the chest wall originating from the heart. This non-invasive method provides information about the mechanical components of the heart. The morphology of the SCG-signal changes in relation to respiration, and understanding these changes will improve the diagnostic value of SCG. The aim of this study was to determine the amplitude of a respiration signal measured through a nasal catheter, using SCG features, for specific time points at mitral closure (MC) and aortic opening (AO) in a three-model comparison. The three proposed methods were multiple regression analysis (MRA), support vector regression (SVR), and a neural network (NN). SCG, Electrocardiography (ECG) and nasal-catheter flow signals were collected from 18 healthy subjects (age 29 ± 6 years). Besides MC and AO were the isovolumic moment (IM), aortic closure (AC) and mitral opening (MO) selected as fiducial points in the SCG-signal. These were found using an automatic algorithm followed by manual verification. Fiducial points amplitudes, frequency components, and timings between these fiducial points formed 12 features. All models were trained on 80% of the data and underwent 10-fold cross validation. Testing was performed on the remaining 20% of the data. Predictions on test data for MC and AO time points, the Pearson correlations coefficient, and sum of squared errors of prediction were: (r_{MC}, r_{AO}, SSE_{MC}, SSE_{AO}) for the following models: NN (0.908, 0.904, 11.71, 12.05), SVR (0.881, 0.833, 18.95, 19.76) and MRA (0.450, 0.437, 51.21, 51.48). These predictive models shows a measurable correlation between the SCG-signal and respiration, which enables modelling of the correlation.

1. Introduction

The clinical applications for seismocardiography (SCG) are promising, providing a simple method for measuring the mechanical properties of the heart [1]. SCG-signals are obtained by measuring vibrations on the chest wall, using an accelerometer placed on the sternum [2]. The morphology of the SCG-signal changes in relation to respiration, and understanding these changes is needed to correctly diagnose diseases [3]. A negative pressure under inspiration results in an increase in preload and increased right ventricle systolic volume, while the left ventricle end diastolic volume and left ventricle systolic volume decreases, and vice versa during expiration. [3]. Current solutions for measuring mechanical properties of the heart include: echocardiography (Echo), computed tomography (CT), magnetic resonance imaging (MRI) and catheter coronary angiography (CCA). A common denominator for these methods is that they are time-consuming and expensive, but their advantage is their diagnostic precision [4–7]. SCG could therefore contribute as a cheaper and less time-consuming alternative. In this present effort, the relationship between respiration and fiducial points in the SCG-signal is modeled in an attempt to investigate the relationship between respiration and the SCG-signal.

2. Methods

Respiration affects the time between fiducial points and the length of cardiac cycles [8], and amplitudes of these also change during respiration [3]. The fiducial points during the systolic complex decrease in amplitude during inspiration and the fiducial points in the diastolic complex increase during inspiration and vice versa during expiration [3]. The interpretation and labeling of SCG-signals used in this paper is illustrated in Figure 1.
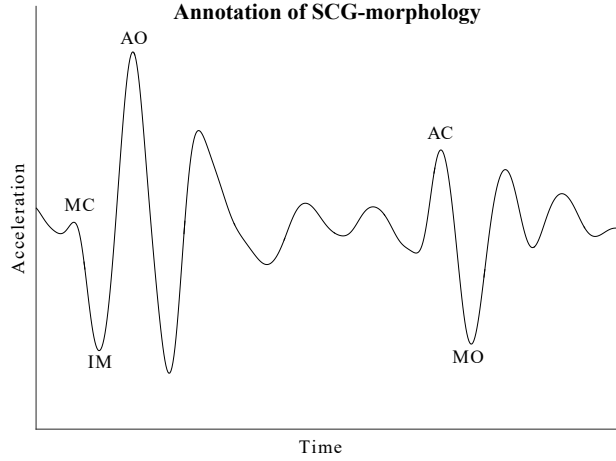
Figure 1. The recording of a dorso-ventral axis SCG-signal, on the Xiphoid Process of a healthy subject. The signal is annotated with: MC (mitral clossure), IM (isovolumic moment), AO (aortic opening), AC (aortic clossure) and MO (mitral opening).

2.1. Feature selection

The features selected for prediction of respiration during cardiac cycles are listed in Table 1. Timings and amplitudes were included as features since these changes during respiration [3, 8]. The power, mean- and median frequencies of the signal between MC and MO are also used as features, since the frequencies change as a result of respiration [3, 9].

Amplitude of	Timing between MC and	Frequency
MC	IM	Mean Freq
IM	AO	Median Freq
AO	AC	Power
AC	MO	
MO		

Table 1. Overview of the selected features for each cardiac cycle, which include five amplitudes, four timings, and three frequency measures.

2.2. Subject data

The SCG-, electrocardiography (ECG)-, nasal spirometer signals were collected from 18 healthy subjects (age: 29 ± 6 years, height: 171 ± 8 cm and weight: 69 ± 12 kg). Data acquisition was performed in the Aerospace Physiology lab in the Department of Biomedical Physiology and Kinesiology. The experimental protocol was approved by the research ethics board of Simon Fraser University as a minimum risk. All participants signed the informed consent form before any experimentation.

2.3. Data acquisition and pre-processing

SCG was recorded on the Xiphoid Process using an accelerometer, respiration flow signals were collected using a nasal-catheter and the ECG was acquired in a lead II configuration using Lifepak8 system (Medtronic Inc, MN, USA). All signals were obtained using NI 9205 analog input module (National Instruments Inc, TX, USA) at a sampling rate of 1000 Hz. An algorithm was implemented in MATLAB to locate the fiducial points of the SCG-signal automatically. The implemented algorithm was inspired by the work of Jafari et al. [10]. The SCG-signal was filtered with low-pass and high-pass filters with cutoff frequencies at 10 and 60 Hz, respectively. Filter frequencies were based on the performance of the peak finding algorithm since the algorithm performed better when finding fiducial points in higher frequency bands. The algorithm found MC, IM, and AO by using local peak detection within windows, which were based on the timing of the R-peak from the ECG-signal. When these fiducial points were found, the AC and MO were found by using search windows which started 300 ms after AO. The annotation of all data was manually verified to ensure correct annotation. Periods of apnea and unrecognisable fiducial points were discarded if the respiration or the SCG-signal was distorted. Only cardiac cycles with all five fiducial points included were used in the data analysis. Out of 12.000, 6.010 cardiac cycles and their corresponding respiration measurements remained, and were normalised using the minimum and maximum values for each subject to make the samples comparable across different subjects.

2.4. Models

Three methods were proposed; multiple regression analysis (MRA), support vector regression (SVR) and neural network (NN). These methods were chosen from the perspective of starting with simple models moving towards more complex models. The data used for the models was divided into training and test sets, of 80% and 20% respectively. Cross-validation with 10 folds was used to validate the models.

The MRA model was applied by using the least square method. No hyperparameters were tuned.

Hyperparameters for the SVR models were found using Bayesian optimisation. Two separate SVR models were trained for predicting the measured respiration amplitudes at MC and AO. For both models, an rbf kernel was used, and the models were applied with an epsilon value of 0.03. The MC model had a C-value of 32.51 and a γ-value of 12.71. The AO model had a C-value of 29.07 and a γ-value of 12.07.

A dense neural network was implemented in Python (Keras 2.0 - TensorFlow backend). Several hyperparam-

eters were found by doing a hyperparameter search, which adjusted the number of units per layer, the number of hidden layers, optimisers, learning rates, etc. The network consists of one input layer, two hidden layers with 128 units using ReLu, two dropout layers with a 40% dropout rate between the two hidden layers. The last layer consisted of two nodes with linear activation functions. A mean squared loss function was used. The model was optimised using an Adam optimiser. The learning rate was lowered 80% when the loss started to plateau.

2.5. Statistical analysis

The measure of linear correlation between actual and predicted respiration was assessed using the Pearson correlation coefficient and sum of squared errors of prediction (SSE).

3. Results

Table 2 shows the mean-values of the cross-validation for all models. According to Table 2, the NN model scored the highest r values (0.908 and 0.904), whereas the SVR model scored lower r values (0.842 and 0.833). The linear MRA model scored the lowest r-values (0.438 and 0.450). An example of the predictions is illustrated in Figure 2. The standard deviations were similar for MC and AO in the cross-validation for SVR and NN, but different for MRA. The SSE for the predicted MC and AO respiration states can be seen in Table 2.

(a) **MC-timepoints**			
	r	mean*	SD*	SSE
MRA	0.438	0.477	0.047	51.21
SVR	0.842	0.826	0.030	18.95
NN	0.908	0.916	0.006	11.71

(b) **AO-timepoints**			
	r	mean*	SD*	SSE
MRA	0.450	0.480	0.043	51.48
SVR	0.833	0.838	0.030	19.76
NN	0.904	0.910	0.006	12.05

Table 2. The table contains (a) mitral closure and (b) aortic opening results from validation and tests of the MRA, SVR, and NN models, r is the Pearson correlation coefficients obtained from models run on the test set. Mean r-values from k-folding, the standard deviation (SD) and SSE scores obtained by the different models. *Validation results.*

4. Discussion

The main finding of this study is that respiration amplitudes can be accurately predicted using cardiac related features from an SCG-signal. The predicted was most accurate in the NN model with high correlation between actual and predicted respiration amplitudes with r-values of 0.904 and 0.908, for the MC and AO time points respectively. Respiration values where not equally distributed when accessing the data. This is because the inspiration and expiration phases are very short, which means that most of the cardiac cycles reside in an inspirated or expirated state. Figure 2 shows that it was possible to predict the respiratory amplitudes for a cardiac cycle located in the inspiration phase. This is clear since the NN predictions are very close to the actual respiratory amplitudes at the MC and AO fiducial points.

The NN model scored the highest Pearsons correlation coefficient (r = 0.908), which means there was an almost linear relationship between the predicted respiration and the actual respiration. This suggests that the relationship between SCG features and respiration is not entirely linear since the MRA model scored much lower r-values than the non-linear models. The low SSE of the NN model indicates that the errors, when predicting the respiration, are relatively small compared to the other models. The similar r-value and mean-value of the NN model, with a small standard deviation, indicates that the model is the most accurate of the three. The accuracies of the three models were evaluated by cross-validating to investigate how well they generalised.

There was a slight increase in accuracy when predicting the respiration amplitude for the MC fiducial point compared to AO fiducial points for all models. It was not possible to find an explanation for this in the data nor from a physiological point of view.

5. Limitations

The validity of the features can be questioned, especially those that were related to the annotated cardiac fiducial points. The annotations of the fiducial points were verified manually, without clinical expertise and with ECG as a reference, as opposed to echocardiography, which is the gold standard. Another limitation was the data size and distribution. Few samples were located on the ascending and descending slopes of the respiration, while the bulk of data samples were in the peak and valley plateaus. The results of the models could be optimistic since there might have been a leak in information between training and test data. Training data not similar to the test data would give a more realistic prediction. The order of cardiac cycles was randomised and subsequently divided into training- and test set. This approach may have caused information
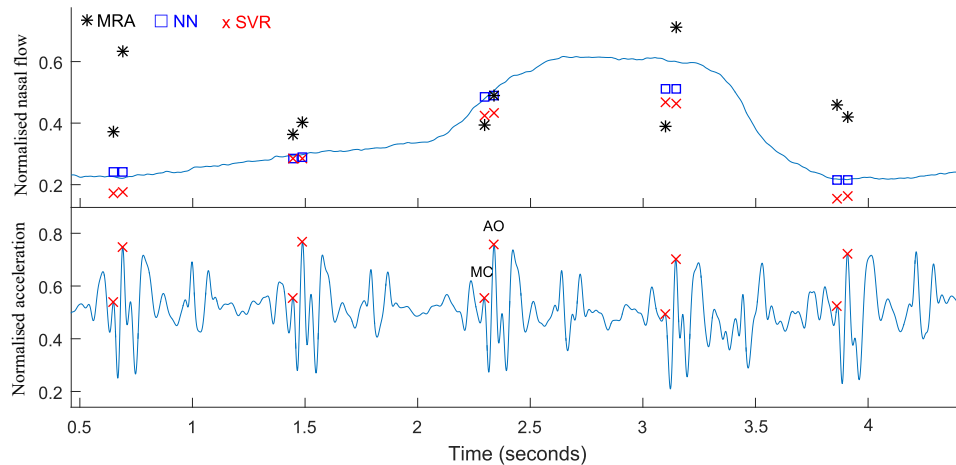
Figure 2. Segment of a normalised respiration signal and the corresponding SCG-signal for a single subject. In the top figure, the predicted values are marked on the respiration signal from the Multiple Regression Analysis, Support Vector Regression, and Neural Network models. The SCG-signal is annotated with the fiducial points of MC and AO respectively.

to leak from the training sets into the test set and thereby lead to a more optimistic result. A validation method to accommodate that issue could be "Leave One Subject Out" cross-validation. This method was not used due to time constraints.

6.   Conclusion

The models based on the proposed methods showed the ability to predict the respiratory amplitudes with respects to MC and AO. The non-linear, NN and SVR, models proving the most accurate approaches and it was found that the SCG-signal does contain information regarding respiration. Predicting the respiration from the SCG-signal with these models, makes it possible to distinguish the respiratory states and perform segmentation of SCG-signals based on respiration.

References

[1] Inan OT, Migeotte PF, Park KS, Etemadi M, Tavakolian K, Casanella R, Zanetti J, Tank J, Funtova I, Prisk GK, Di Rienzo M. Ballistocardiography and Seismocardiography: A Review of Recent Advances. IEEE 2015;19(4):1414–1427.

[2] Tavakolian K. Characterization and Analysis of Seismocardiogram for Estimation of Hemodynamic Parameters. Doctoral dissertation 2010;215.

[3] Amit G, Shukha K, Gavriely N, Intrator N. Respiratory modulation of heart sound morphology. AJP 2009;296(3):H796–H805.

[4] Wick CA, Su JJ, McClellan JH, Brand O, Bhatti PT, Buice AL, Stillman AE, Tang X, Tridandapani S. A system for seismocardiography-based identification of quiescent heart phases: Implications for cardiac imaging. IEEE 2012;16(5):869–877.

[5] Nikolaou K, Alkadhi H, Bamberg F, Leschka S, Wintersperger BJ. MRI and CT in the diagnosis of coronary artery disease: indications and applications. I 2011;2(1):9–24.

[6] Mant J, Al-Mohammad A, Davis M. CHRONIC HEART FAILURE: National National clinical guideline for diagnosis and management in primary and secondary care. NCGC 2010;108(108):1–119.

[7] Mertens L, Friedberg MK. The gold standard for noninvasive imaging in congenital heart disease: echocardiography. Curr Opin Cardiol 2009; 24(2):119–24.

[8] Inan OT, Pandia K, Giovangrandi L, Zamanian RT, Kovacs GTA. A preliminary study investigating the quantification of beat-to-beat in seismocardiogram signals. EMBS 2013;7286–7289.

[9] Zakeri V, Akhbardeh A, Alamdari N, Fazel-Rezai R, Paukkunen M, Tavakolian K. Analyzing Seismocardiogram Cycles to Identify the Respiratory Phases. IEEE 2017;64(8):1786–1792.

[10] Jafari Tadi M, Koivisto T, Pänkäälä M, Paasio A, Knuutila T, Teräs M, Hänninen P. A new algorithm for segmentation of cardiac quiescent phases and cardiac time intervals using seismocardiography. volume 9443. mar 2015; 94432K.

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