Detecting Aortic Stenosis Using Seismocardiography and Gryocardiography Combined with Convolutional Neural Networks

Ismail Elnaggar[1], Tero Hurnanen[1], Olli Lahdenoja[1], Antti Airola[1], Matti Kaisti[1], Tuija Vasankari[2], Jouni Pykäri[2], Mikko Savontaus[2], Tero Koivisto[1]

[1]University of Turku, Department of Computing, Turku, Finland
[2]Turku University Hospital, Turku, Finland

Abstract

Aortic Stenosis (AS) is a heart valve disease characterized by the narrowing of the aortic valve opening. Currently AS is primarily diagnosed using echocardiography performed by a trained specialist. We aimed to evaluate the ability of non-invasive microelectromechanical system (MEMS) based seismocardiography (SCG) and gyrocardiography (GCG) sensors to detect AS in individual cardiac cycles in subjects by measuring the cardiac-induced vibrations produced by the mechanical activity of the heart.

Data was collected from 20 AS subjects and 51 healthy subjects using a custom data logger capable of measuring SCG, GCG, and single-lead ECG. The captured SCG and GCG signals were segmented into individual cardiac cycles. A continuous wavelet transform was applied to produce time-frequency representations of each cardiac cycle. Each SCG and GCG axis of motion was then overlaid and fed as an input to a convolution neural network (CNN). Using leave-subject-out cross validation, the model produced specificity of 98.42%, sensitivity of 98.14%, and average accuracy of 98.36%.

1. Introduction

Cardiovascular diseases (CVDs) are the number one cause of death globally. In the year 2016, an estimated 18 million people died from CVDs [1]. It is projected that by the year 2035, over 130 million adults in the US alone will have some form of CVD, with total costs of treatment related to CVDs expected to reach $1.1 trillion [2]. AS is the most common heart valve disease and the third most common CVD behind hypertension and coronary artery disease. It is also the most common reason for aortic valve replacement procedures [3]. Patients with asymptomatic AS have a survival rate comparable to that of age-matched healthy control patients. The survival rate rapidly decreases after symptoms begin to appear. The primary diagnostic test used to identify AS is transthoracic echocardiography performed by a trained specialist [4].

The goal of this work is to investigate the suitability of SCG and GCG to detect aortic stenosis earlier and without the need of trained specialist to carry out physical examinations on patients. By combining sensor technology and machine learning techniques to create a system to detect AS earlier, we may be able to help clinicians identify AS earlier than with standard methods used today alone.

2. Methods and Materials

Figure 1 gives an overview of the overall pipeline used from data acquisition to model training.

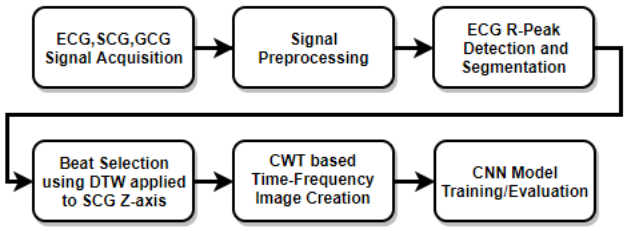

Figure 1: Overall pipeline of proposed method

A custom data logger was used to capture time-series signals from the subjects. Three-axis SCG signals were measured with a MEMS based accelerometer (ADXL355 Analog Devices) while the three-axis GCG signal was measured using a 3D digital accelerometer and gyroscope system (LSM6DS3 STMicroelectronics), where only the gyroscope signal was used. Single lead ECG signal was measured using a MAX30003 (Maxim Integrated).

After the signals were captured, the ECG signal was filtered to remove any noise to be able to automatically detected the R-peak locations in order to segment the SCG and GCG signals. R-peak detection was performed in python3.8 using the Neurokit2 python library with the default R-peak detection algorithm [5].

After R-peak detection, the SCG and GCG signals were segmented into individual cardiac cycles based on the detected RR-intervals. Once segmentation is complete, the cardiac cycles that were most similar to each other based

on the Z-axis of the SCG signal, were selected while the rest of the cardiac cycles were discarded.

The saved cardiac cycles were then processed using a continuous wavelet transform (CWT). The output of the CWT produced a time-frequency matrix representation of each cardiac cycle. The CWT was applied to each axis of the SCG and GCG signal and then the matrices were overlaid to form an image that contained six channels representing each axis of motion from the SCG and GCG signals.

2.1. Dataset

A total of 72 subjects were collected for this study between May 2018 to December 2020. 21 subjects who had been diagnosed with severe aortic stenosis and 51 healthy control subjects who were known to have no prior cardiovascular issues. One patient diagnosed with AS also suffered from atrial fibrillation so they were excluded from the model development leaving 71 subjects to train and test the model. The 20 AS subjects used for model development were collected at the Turku University Hospital and consisted of 10 male and 10 females and had an average age of 78.

The healthy control group was collected at the digital health technology lab at the University of Turku and no age or sex information was gathered. The control group mainly consisted of students and faculty from the University of Turku and as such, the subjects were much younger and comparable in age to the control group in a related study concerning AS classification by Yang et al. [6].

2.2. Signal processing

ECG, SCG, and GCG were acquired at the following sampling frequencies: 128, 416, and 208 Hz. The signals were then synced and resampled to 200Hz. SCG and GCG signals were band pass filtered using a zero phase 4th order Butterworth filter with cutoff frequencies of 1 to 65 Hz. The low pass value of 65 Hz was selected because of the digital low pass filter implemented in the LSM6DS3 gyroscope which limits the signals frequency content to 66.7 Hz. The signals were then normalized by dividing each channel by its standard deviation. Filtering performed on the SCG and GCG signals was performed using the SciPy python library.

The ECG signal was high pass filtered using a 5th order Butterworth filter with a cutoff frequency of 0.5 Hz. This was performed using the default parameters from the "ecg_clean" function from the NeuroKit2 python library.

2.3. Segmentation and Beat Selection

When measuring SCG from a subject the signal's morphology and frequency components can vary from one cardiac cycle to the next [7]. To eliminate this variability within a subject's measurement the beats can be separated depending on their similarity. Another issue can occur if noise is present in the ECG signal during acquisition. This can cause the peak detection algorithm's accuracy to be effected. We can address both of these issues by performing beat selection.

An R-peak detection algorithm "ecg_findpeaks" from NeuroKit2 was used with default parameters. After the SCG and GCG signals were segmented based on the detected R-peak locations, a grouping method based on dynamic time warping (DTW) [8] using the python implementation of the FastDTW [9] library was implemented using the Z-axis SCG signal. The following steps were performed to select the beats with the highest similarity. This method was inspired by a similar method from Dehkordi et al. [7].

1. For all cardiac cycles in a single measurement, calculate the DTW distance measure DTW_D, between all cycles using the Z-axis of the SCG signal.
2. The output is an n *n*-by-n matrix where n is equal to the number of cycles in the recording. Each entry in the matrix will correspond to the DTW_D between two given cycles while the leading diagonal of the matrix contains zero values because of the distance measure calculation between a given cycle and itself.
3. Compute the average value of each column, which measures the average DTW_D of a given cycle to all other cycles.
4. Select the cycle with the minimum average DTW_D measurement DTW_{AvMin}; consider that cycle to be SCG_{minD}.
5. Calculate DTW_D between SCG_{minD} and all other cycles.
6. If DTW_D between SCG_{minD} and a given cycle is less than $DTW_{AvMin,}$ select that given cycle, otherwise the cycle is removed.

This process ensures that cardiac cycles that possibly contain noise such as motion artifacts or are not true cardiac cycles because of errors produced during RR-interval detection are excluded. One notable drawback of this method is the assumption that the overall signal quality of the recording is acceptable. If the SCG recordings have a low signal to noise ratio this method may perform poorly.

Figure 2 below shows a plot from one patient, which highlights the morphological differences in the selected and discarded cardiac cycles for one patient. The green and red plots represent the selected and discarded beats, while the black signal represents the ensemble average of all the beats for each group.

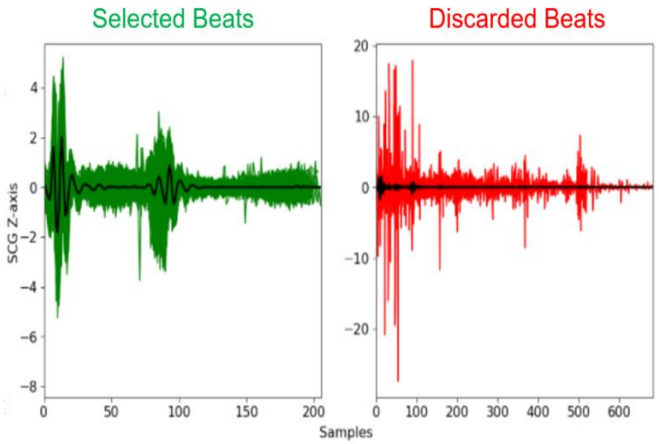

Figure 2: Overlaid selected and discarded cardiac cycles from a subject diagnosed with AS. The plotted Z-axis SCG signals are band pass filtered between 20-99 HZ for visualization purposes.

For the subject shown in Figure 2, 373 cardiac cycles were analyzed. After applying the proposed beat selection method, 55 beats were discarded, leaving a total of 318 cardiac cycles. When plotting the selected and discarded beats for different subjects a few common patterns appeared across the dataset.

Firstly, the selected beats share a more uniform pattern and the ejection period of the cardiac cycles can be roughly estimated by looking at the two large peaks present in the green plot. When examining the lengths and amplitudes of the cardiac cycles between the two groups of beats we notice differences as well. In the green plot, the amplitude across the cardiac cycles do not present many random peaks that could be associated with noise. While we see large amplitude spikes in the red plot of discarded beats. The length of time of the cardiac cycles between the two groups vary greatly as well. This could be due to poor ECG signal quality or motion artifacts during signal acquisition causing the R-Peak detection algorithm to fail for certain cycles.

2.3. Time-Frequency Image Representation

Time-frequency representation of different kinds of time series data has become a popular type of data input for CNNs. Yang et al. [10] converted 10-second segments of single axes of SCG into 1-D images as inputs to CNNs. Torres et al. [11] applied CWT to 1.2 second windows of ECG data in order to convert the time series data to time-frequency representations to be later fed into a CNN as well.

Individual cardiac cycles were converted into time-frequency matrices using the continuous wavelet transform with the Morlet wavelet selected as the mother wavelet. Each axis of the SCG and GCG signals were converted into time-frequency matrix representations of their axis of motion and then were overlaid to form an image of dimensions *H*-by-*W*-by-*D*. *H* represented the height of the image which was determine by selecting a fixed amount of scales, *W* representing the width of the image which is the length of the cardiac cycle, and D representing the depth of the image which would be the 6 axes of motion captured by the SCG and GCG signals.

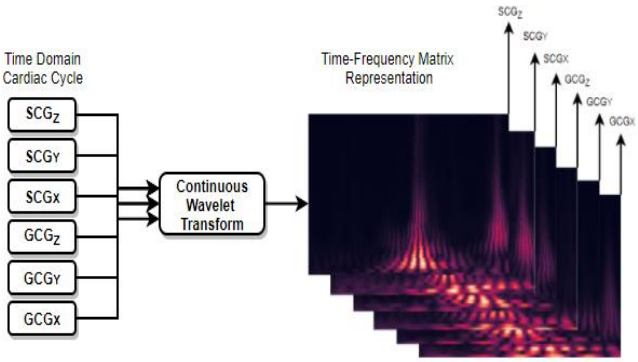

Figure 3: Overview of cardiac cycle transformation to a time-frequency matrix image with six channels. Selected colors for time-frequency image used for visualization purposes only.

The CWT was performed in python using the PyWavelets [12] python library. 25 scales representing frequencies between 1 to 65 Hz were selected for the height of the image. This frequency range is equivalent to the passband of the filter applied before applying CWT. For different subjects the dominant frequency can vary across a wide range of frequencies [13] so the decision was made to capture frequency content from the entire available pass band. Castiglioni et al. [14] suggest that frequencies above 18 Hz may be related to valve closures, while lower frequencies may relate to heart contraction. By selecting scales that cover these frequencies ranges it may be possible to differentiate between cardiac cycles that show poor heart and valve function.

After all cardiac cycles were converted to images, the images were resized to a fixed dimension of 25-by-120-by-6 and normalized to values between 0 and 1. Resizing was necessary in order to perform mini-batch training for the CNN model developed for this method.

2.4. CNN Model Description

CNNs have been a proven method in the task of image classification and have been used in tasks concerning bio signal time series classification such as [10][11]. CNNs can extract features from time-frequency image representations, which can capture morphological changes in cardiac cycles between healthy and diseased individuals. Figure 4 gives a visualization of the CNN architecture used in this study. This architecture is a simple CNN with only convolutional layer. A simple architecture was chosen to reduce complexity and prevent overfitting.

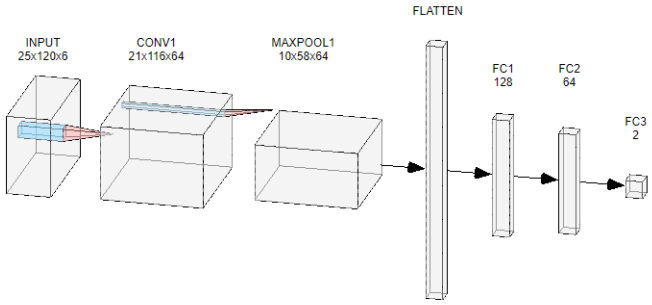

Figure 4: A 3D summary view of the proposed CNN architecture. The dimensions are given at each layer of the network.

The CNN was developed using TensorFlow and consisted of one convolutional layer with 64 filters and a kernel size of 5 and a stride of 1 with a ReLU activation function. A drop out of 0.2 was applied to the output of the first convolution. This was followed by a max-pooling layer with a pool size of 2. After pooling the feature maps were flattened and fed into 2 consecutive fully connected layers of size 128 and 64 both with ReLU activation functions. Finally, the output of the FC2 layer was fed into an output layer with a softmax activation to produce a decision. Training was performed over 30 epochs with a learning rate of 8e-5 using the ADAM optimizer with the loss function being set to categorical cross entropy.

3. Model Evaluation and Results

A leave-subject-out cross validation approach was chosen to estimate the models performance. Each subject and the cardiac cycles associated with that subject was used as a test set while a new model was trained using the remaining subjects and their cardiac cycles. The true and predicted values from each round of cross-validation were pooled together. For the AS class, precision, recall, F1-score, and average accuracy per subject were the following: .95, .98, .96, and .98 for 7706 cardiac cycles. For the healthy control class, precision, recall, F1-score and average accuracy per subject were: .99, .98, .99, and 98 for 26770 cardiac cycles. Table 1 shows that the proposed method performs on par compared to a similar study concerning AS classification when using a healthy population as the control group.

Table 1: Comparison of classification results between AS subjects and healthy controls.

Method	Statistics		
	Specificity	Sensitivity	Accuracy
Proposed Method	**98.42**%	**98.14**%	**98.36**%
[6]	98.18%	97.27%	97.73%

4. Conclusion

The proposed method was able to perform well when separating between AS patient cardiac cycles and health control group cardiac cycles. One main limitation of this study is the lack of an age and sex matched control group. A new age and sex matched control group will need to be gathered to further validate the proposed approach with a more realistic control set.

References

[1] World Health Organization, "Cardiovascular diseases (CVDs) [fact sheet]", Retrieved 20 August 2021, from https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

[2] Benjamin et al., "Heart disease and stroke statistics – 2018 update: a report from the American Heart Association", *Circulation*, vol. 137, no. 12, pp. 67–69, Mar. 2018.

[3] Nathaniel S, Saligram S, Innasimuthu AL., "Aortic stenosis: an update", *World J Cardiol.* vol 2, no. 6, pp. 135-139, Jun 2010.

[4] Grimard et al., "Aortic stenosis: diagnosis and treatment" *Am Fam Physician*, vol. 95, no. 5, pp. 371– 378, Mar. 2016.

[5] Makowski, D., Pham, T., Lau, Z.J. et al., "NeuroKit2: a python toolbox for neurophysiological signal processing" *Behav Res*, vol. 53, pp. 1689-1696, Feb. 2021

[6] C. Yang, N. D. Aranoff, P. Green, N. Tavassolian, "Classification of aortic stenosis using time–frequency features from chest cardio-mechanical signals," *IEEE Trans Biomed Eng*, vol. 67, no. 6, pp. 1672-1683, June 2020.

[7] Dehkordi et al., "Identifying patients with coronary artery disease using rest and exercise seismocardiography" *Front. Physiol*, vol. 10, no. 1211, Sept. 2019

[8] D. Berndt and J. Clifford, "Using dynamic time warping to find patterns in time series", *AAAIWS*, Vol 3. pp.359-370, July 1994.

[9] S. Salvador, and P. Chan. "FastDTW: toward accurate dynamic time warping in linear time and space", *Intelligent Data Analysis*, vol.11, no.5, pp. 561-580, 2007

[10] Yang, C., Ojha, B.D., Aranoff, N.D. et al., "Classification of aortic stenosis using conventional machine learning and deep learning methods based on multi-dimensional cardio-mechanical signals", *Sci Rep*, vol 10., Oct 2020, Art. no. 17521

[11] J. Torres, K. De Los Rios, M. Padilla, "Cardiac arrhythmias identification by parallel CNNs and ECG time-frequency representation", *CinC*, vol. 47, Sept. 2020.

[12] G. Lee et al., "PyWavelets: a python package for wavelet analysis", *JOSS*, vol. 4, no 36, April 2019.

[13] A. Taebi and H. Mansy, "Time-frequency distribution of seismocardiographic signals: a comparative study", *BioEng*, vol. 4, no. 2, April 2017.

[14] Castiglioni et al., "Wearable seismocardiography", *EMBC*, vol. 29, pp. 3954-3957, Aug. 2007.

Address for correspondence:
Ismail Elnaggar
Kiinamyllynkatu 10, 20520, Turku, Finland
imelna@utu.fi