Cardiac Time Intervals Derived from Electrocardiography and Seismocardiography in Different Patient Groups

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

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

Abstract

Differences in cardiac time intervals (CTIs) have previously been shown in different patient groups with varying levels of cardiac function. These studies relied on methods such as conventional echocardiography or tissue doppler imaging performed by a specialist to extract CTIs. The goal of this study was to evaluate the ability of using a combination of single lead ECG and 3-axis seismocardiography (SCG) from a sensor placed on a subject's sternum to automatically extract CTIs.

For each subject, pre-ejection period (PEP), left ventricular ejection time (LVET), total systolic time (TST), and total diastolic time (TDT), which were normalized by the mean heart rate representing the entire recording were extracted using a custom developed algorithm.

LVET was on average 20.5 % shorter in the NKHCD group vs PRE-TAVI ($p < 0.05$) and 5.9% shorter in the HCD group vs PRE-TAVI ($p > 0.05$). Comparing CTIs between the subjects who had data recorded before and after receiving a TAVI procedure, a 12.6% postoperative reduction in LVET ($p < 0.05$) was found on average as well as a 30.2% increase in PEP/LVET ($p < 0.05$).

These results are in line with literature where LVET increases with age and severe aortic stenosis and decreases after TAVI procedures when echocardiography was the main methodology used to extract CTIs.

1. Introduction

Cardiac time intervals (CTIs) have been investigated for a number of years as a marker for poor cardiac function primarily with methods such as echocardiography or tissue Doppler imaging [1]. CTIs for example have been shown to identify poor cardiac functions in individuals with hyptertension as well as be a predictior of future cardiocasvular disease in individuals with hyptertension [2]. Changes in CTIs have been shown to have a relationship with all-cause mortality. Haiden et al [3] showed that a U-shaped relationship with changes to LVET meaning both a shortening and a lengthening in LVET was associated with all all-cause mortality. Different cardiovascular diseases can cause different changes in the duration of CTIs. Patients with aortic stenosis have been shown to have prolonged LVET. The cause for this is not fully understood as of yet [4]. While it has also been shown that shortening of LVET increases the risk of mortality in patients with heart failure with reduced ejection fraction [5].

All of the aforementioned methods used complex imaging techniques performed in clinics to produce CTIs. Methods have also been proposed using a combination of ECG and SCG to extract CTIs [6] but showed degraded performance in patient groups with a history of heart disease. One challenge with identifying CTIs in patients with different cardiovascular diseases is that the typical morphology of the signal can vary significantly. This makes it challenging to accurately identify events such as the aortic opening (AO) and aortic closing (AC) in an SCG waveform. This is especially true for diseases like aortic stenosis (AS), where the AC component of a SCG signal can be almost unidentifiable. The purpose of this study is to provide a simple reproducible method that calculates modified CTIs from ECG and SCG signals that have been tested on different groups with different levels of cardiac function and show that the results are in line with results shown in literature when the main measurement method was either echocardiography or tissue Doppler imaging. The following four CTIs were considered in this study, defined by time differences between the following events:

1. PEP = AO – R-Peak
2. LVET = AC – AO
3. TST = AC – R-Peak
4. TDT = R-Peak_{N+1} – AC

Figure 1 below illustrates these points using an example cardiac cycle.

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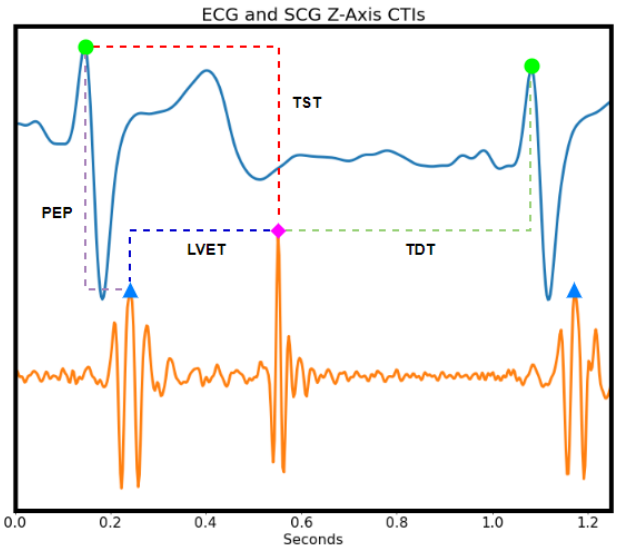

Figure 1: CTIs labeled using a single cardiac cycle. SCG Z-axis band-pass filtered between 20 and 100 Hz.

The R-peaks in Figure 1 are represented by green dots while the AO is represented by blue triangles and the AC is marked with a pink diamond.

2. Methods and Materials

Figure 2 gives an overview of the pipeline to extract CTIs from raw ECG and SCG recordings. After ECG and SCG signals were captured they were first visually inspected to ensure good data capture. Afterwards the ECG signal was filtered to eliminate noise that may hinder the accuracy of the R-Peak detection algorithm to correctly identify R-peak locations from the ECG signal. R-peaks were detected using the default peak detection algorithm provided by the NeuroKit2 python library.

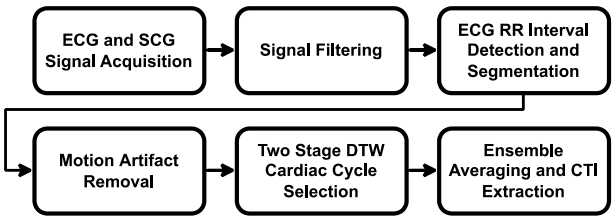

Figure 2: Overall pipeline of proposed method.

After R-peak detection, the SCG signals were segmented into individual cardiac cycles based on the detected RR-intervals. Once the cardiac cycles were segmented, only the Z-axis of the SCG signal was used. This decision was made after initial testing showed that the Z-axis of the SCG signal produced the clearest ensemble average waveforms when extraction of CTIs was performed.

After segmentation, artifacts in the segmented SCG Z-axis signal such as motion artifact amplitude spikes were removed by using a median RMS thresholding technique similar to [7]. The remaining cardiac cycles were then grouped using a two stage dynamic time warping (DTW) similarity measure which is an improvement based on a technique used in our prior work [8]. The selected cardiac cycles were then ensemble averaged to produce a final representation of a cardiac cycle and then a simple peak detection algorithm was used to find peaks that were located closely to where the AO and AC were believed to be. Modified CTIs were extracted using the R-peak as a substitute for the Q-wave in the QRS complex.

2.1. Dataset

The dataset used in this study consists of 157 subjects collected using a custom data logger device which collected single lead ECG, 3-axis SCG, and 3-axis GCG signals. In this study only the ECG and Z-axis SCG signals are considered. More information about the data acquisition device can be found in [9]. The 157 subjects who were collected for this study were split into four different categories.

The first group consists of younger subjects with no known history of cardiac disease (abbrv: NKHCD, N = 51, Mean Age = NA, # of Males = NA). The second group of subjects consists of older subjects with a history of cardiac disease excluding valve heart disease (abbrv: HCD, N = 49, Mean Age = 66 ±10.3, # of Males = 39). The third group of consists of subjects who have been diagnosed with severe AS. This group is divided further into measurements taken before a transcatheter aortic valve implantation (TAVI) procedure (abbrv: PRE-TAVI, N = 57, Mean Age = 79 ±6.1, # of Males = 26), and measurements taken after a TAVI procedure (abbrv: POST-TAVI, N = 23, Mean Age = 76 ±5.0, # of Males = 12) The POST-TAVI group is 23 subjects taken from the PRE-TAVI group.

The measurements for the NKHCD group were taken at the department of computing at the University of Turku and no age and sex information was gathered. These subjects were younger in age and were mostly students and faculty from the university. The HCD, PRE-TAVI, and POST-TAVI measurements were taken at the Turku University Hospital. Health care providers who took the measurements were unable to take more POST-TAVI measurements due to time constraints or the patients were discharged before the measurement could be taken. Measurements were on average 9 minutes in length.

2.2. Signal processing

ECG and SCG were acquired at 128 and 416 Hz. The signals were then synced and resampled to 400 Hz. The SCG Z-axis signal was then band pass filtered using a zero phase 8th order Butterworth filter with cutoff frequencies of 20 to 100 Hz. These cut off frequencies although unconventional, provided the best peak locations when ensemble averaging the signals together. The signal was subtracted by its mean value then normalized by dividing it by its standard deviation. Filtering performed on the SCG Z-axis signal 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. Motion Artifact Removal

When DTW is applied to SCG cardiac cycles the accuracy of the similarity measure employed in this study is reduced when noise such as amplitude spikes are present throughout the recording. In order to remove these spikes, we calculate a threshold value automatically for each subject and remove any cardiac cycles whose amplitude cross this threshold value at any point. This threshold is a multiple of the median RMS value calculated across all cardiac cycles. The value is conservative in order to avoid removing any noise free cardiac cycles. This is because the two stage DTW cardiac cycle selection process removes most other cardiac cycles that have been corrupted by noise or are not true cardiac cycles because of errors in R-peak detection.

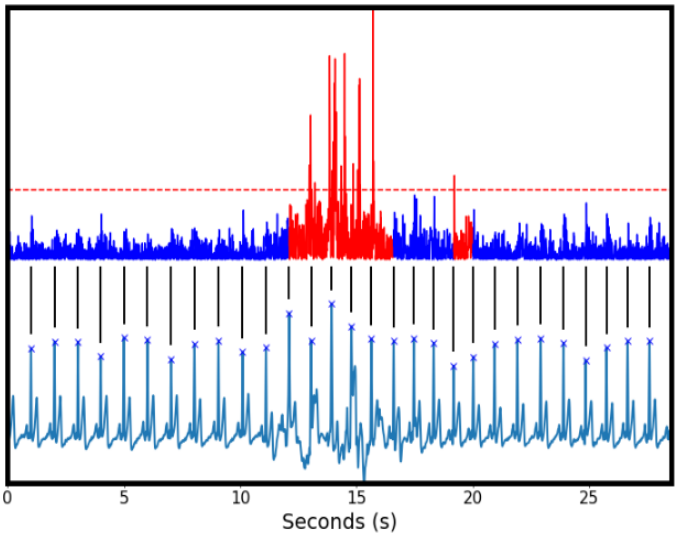

Figure 3: Illustration of motion artifact removal. ECG is shown on the bottom portion of plot while individual cardiac cycles are labeled blue if noise free or red if they contain noise.

Figure 3 shows an example of 30 consecutive cardiac cycles with the SCG Z-axis signal present on the top and the ECG signal with R-peaks denoted on the bottom. The artifact free portions of the signal are colored blue while any cardiac cycles in the SCG signal that are deemed to contain noise are colored in red.

2.4. Two Stage Dynamic Time Warping

DTW has been previously applied to SCG signals for detection of fiducial points in smaller sample sizes [6][10]. The method used to group the cardiac cycles into similar and dissimilar beats is based off prior work in [8]. The algorithm described in [8] is applied two consecutive times by first creating an initial grouping of accepted and discarded beats as is done in [8] and then applied again to the first round of accepted beats to create a new set of accepted and discarded beats. Please refer to [8] for a more detailed description of the steps used in the algorithm to separate cardiac cycles into different groups. By performing the DTW grouping two separate times, a more accurate ensemble waveform can be created to reliably extract time intervals from. After the two-stage DTW algorithm was applied to all 157 subjects, a total of 54211 cardiac cycles were left for analysis.

2.4. Cardiac Time Interval Extraction

Once the cardiac cycles were grouped, the discarded beats were no longer used for CTI extraction. The accepted beats were then averaged to create a single waveform, which was used to detect the AO and AC events. The following steps were applied to the grouped cardiac cycle to create a final waveform for CTI extraction.

1. For each cardiac cycle in the accepted group the absolute value of the cardiac cycle is calculated creating CC_{Abs}.
2. A convolution function is then applied to CC_{Abs} with a triangle filter with a window length of 20 samples or 50 ms creating CC_{Conv}.
3. Each consecutive CC_{Conv} is then summed together and averaged by the total count of CC_{Conv} creating $CC_{Avg.}$
4. Using the SciPy find_peaks function, the two most prominent peaks in CC_{Avg} are selected to represent the average AO and AC locations for that measurement.

Figure 4 below shows an example of the overlaid SCG cardiac cycles and the resulting CC_{Avg} waveform created to detect AO and AC locations. The reasoning for the triangle filter convolution with CC_{AV} was to boost the prominence

of the AO and AC peaks to make peak detection more accurate.

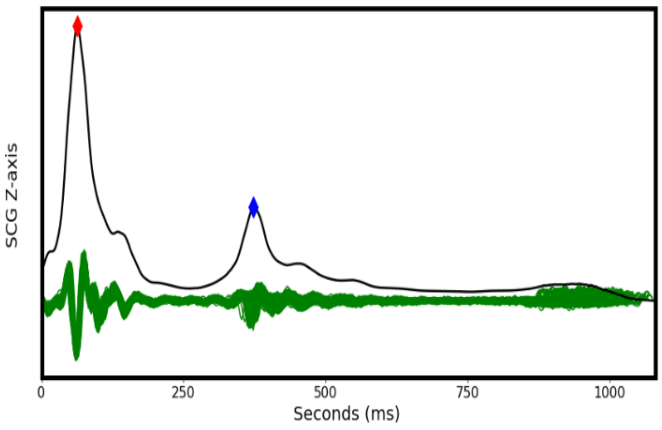

Figure 4: Example of AO (Red Diamond) and AC (Blue Diamond) extraction from CC_{Avg} waveform. Green signal represents the grouped cardiac cycles used to create CC_{Avg}.

3 Results

When applying the proposed method the following results were derived. The mean heart rates were 62.81 bpm, 66.72 bpm, 70.43 bpm, and 70.87 bpm for the KNHCD, HCD, PRE-TAVI, and POST-TAVI groups. The CTIs for each subject are normalized by the average heart rate produced by their ECG record. LVET on average was 20.5% shorter for NKHCD vs. PRE-TAVI ($p < 0.05$) and 15.5% shorter for NKHCD vs. HCD ($p < 0.05$). LVET was 5.9% shorter for HCD vs. PRE-TAVI but was not statistically significant ($p > 0.05$). No statistically significant differences were observed in the CTIs between the HCD vs. PRE-TAVI cohorts in this study using the proposed method.

TDT was on average 15.1% longer for NKHCD vs. PRE-TAVI ($p < 0.05$) and 11.6% longer for NKHCD vs. HCD ($p < 0.05$).

When comparing subjects who had measurements taken before and after TAVI procedures, a 12.6% postoperative reduction in LVET ($p < 0.05$) was found on average as well as a 30.2% increase in PEP/LVET ($p < 0.05$). TDT was shown to increase 6.1% ($p < 0.05$) on average postoperatively. The mean heart rate values in these subjects showed no statistically significant difference ($p > 0.05$). These results are in line with literature where LVET increases with severe AS and age as well as decreases after TAVI procedures [11].

4 Conclusion

These results show promise in using SCG and ECG signals with a simple extraction method to extract CTIs from subjects with cardiac disease when compared to results in previous literature.

Some limitations of this study are the use of the R-peak instead of the Q wave in the QRS complex as the reference point for PEP. Subjects with wide QRS complexes may produce inaccurate PEP values. In addition, a non-standard location for the AC was chosen in this study, this location being the local maxima of the diastolic complex. This was done because of the lack of annotated CTI time interval data and for subjects that suffered from severe aortic stenosis, the AC component can be hard to identify because of changes in the morphology of the diastolic complex due to severe AS.

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