Validation of Algorithm for Automatic Beat-to-Beat Detection of Aortic Valve Opening and Closing

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Abstract

Background & aim: Seismocardiography (SCG) enables non-invasive assessment of cardiac function by capturing chest vibrations associated with physiological events such as aortic valve opening (AO) and aortic valve closure (AC). Reliable detection of these events is essential for clinical applicability. We have earlier proposed a deep learning based algorithm for beat-to-beat detection of, among others, AO and AC (SeismoTracker). The validation in external datasets is of great importance for proving generalizability. Therefore, this study aims to validate beat-to-beat AO and AC detection from external dataset. Method: An open-source data set with 6 pigs undergoing hypovolemia with a total of 81983 individual heartbeats was used. Reference and algorithm detected AO and AC were extracted for comparison. Sensitivity, positive predictive value (PPV), and bias were computed across all pigs for AO and AC. Results: The median (IQR) PPV was 0.968 (0.029) for AO and 0.883 (0.151) for AC. For sensitivity it was 0.473 (0.337) and 0.458 (0.326) for AO and AC, respectively. The bias was 1.48 ms and -11.57 ms for AO and AC, respectively. Conclusion: The algorithm demonstrated generalizability and robustness for beat-to-beat AO and AC detection with high PPV.

1. Introduction

Seismocardiography (SCG) is the method of capturing chest vibrations caused by the beating heart using an accelerometer. The method was first introduced by Mounsey in 1957 [1], and has during the last decades been more widely used due to new accelerometer technologies being invented [2]. Moreover, specific fiducial points in the SCG have been related to physiological events in the cardiac cycle such as opening and closing of valves, peak atrial inflow, and peak systolic outflow [3–6] enabling the signal's clinical applicability. Especially, the timing of aortic valve opening (AO) and aortic valve closure (AC) are of interest as they are clinical interesting parameters and determinant for the first and second heart sound. Therefore, it is of great importance to detect those fiducial points in the SCG consistently across different subjects in order to enable a simple, low-cost, and easy-to-use method to assess a patient's hemodynamic status. Multiple algorithms for AO and AC detection have been suggested; electrocardiography (ECG) and photoplethysmography (PPG) assisted algorithms [7, 8], algorithms relying on predefined decision rules [7, 9–14], and a newer approach using deep learning [15] for fiducial point detection (SeismoTracker). The latter represented promising results in multiple internal datasets, however, it has not yet been validated based on external datasets. External validation is essential to assess the generalizability and robustness of SeismoTracker across different populations and recording conditions. Therefore, the aim of this study is to validate beat to beat AO and AC localization based on SeismoTracker from Korsgaard et al [15] on an external dataset.

2. Method

To validate SeismoTracker on external data, the open-source dataset from Cho et al [16] that consists of catheter based aortic pressure and SCG recordings from pigs undergoing a controlled hypovolemia experiment. SeismoTracker is developed to extract fiducial points on a beat-to-beat basis, and the manual annotations from Cho et al [16] only contained annotations on aligned beats, however, without known alignment to the original signal. Consequently, those annotations could not be used for validation of the beat-to-beat based algorithm. Therefore, the aortic pressure was used for independent reference AO and AC timings.

2.1. Algorithm to Validate

SeismoTracker is an algorithm originally developed for identifying 11 fiducial points in the SCG signal on a beat-to-beat basis. It was originally developed on on human subject data with a conservative detection strategy. The algorithm was designed to identify either all 11 fiducial points within a cardiac cycle or neither, thereby avoiding partial detections. Furthermore, fiducial points are reported only when the model's confidence exceeds a predefined threshold, ensuring that only high-certainty estimates are included. Furthermore, the algorithm is developed on SCG signals obtained from lower part of the sternum. A detailed description of the algorithm is provided in [15]. In accordance with [6], the points Gs and Bd from SeismoTracker corresponded to AO and AC, respectively, and those timings from SeismoTracker were thus used to obtain AO and AC timings on a beat to beat basis.

2.2. Available Data

The external dataset contained recordings from pigs undergoing a controlled hypovolemia experiment. The dataset includes electrocardiography (ECG), seismocardiography (SCG) recorded at midsternum and apex, phonocardiography from midsternum and apex, femoral photoplethysmography (PPG), femoral oxygen saturation, as well as invasive pressure measurements including aortic pressure, femoral pressure, pulmonary capillary wedge pressure, and right atrial pressure. Only aortic pressure, ECG, and midsternum SCG were used in this study. Aortic pressure was used for reference AO and AC extraction, ECG for synchronization, and SCG for algorithm estimation of AO and AC. SCG from midsternum was used, as this corresponds to the anatomical site for which SeismoTracker was originally developed.

2.2.1. Data Synchronization and Reference AO and AC Detection

SCG and aortic pressure in the external dataset were recorded with two different systems. Even though the sample rate was the same across the two systems, a small drift occurred over time. Therefore, the signals from the two systems were synchronized by detecting the R-peaks in the two signals using Pan Tompkins algorithm [17].

As figure 1 illustrates, the reference beat-to-beat AO and AC detections were identified in the aortic pressure signal following the methodology described in [16] for each beat detected by R-peak, however, with AO adjusted to the aortic pressure valley preceding the AO peak identified in the 2nd derivative. To comply with the requirement of the AO being a peak in the SCG signal [6] and as indicated in segmented beats annotations in [16], the AO is snapped to nearest peak in the SCG signal. In summary, both reference and predicted AO and AC timings were identified in the SCG signal, enabling direct temporal validation of SeismoTracker.

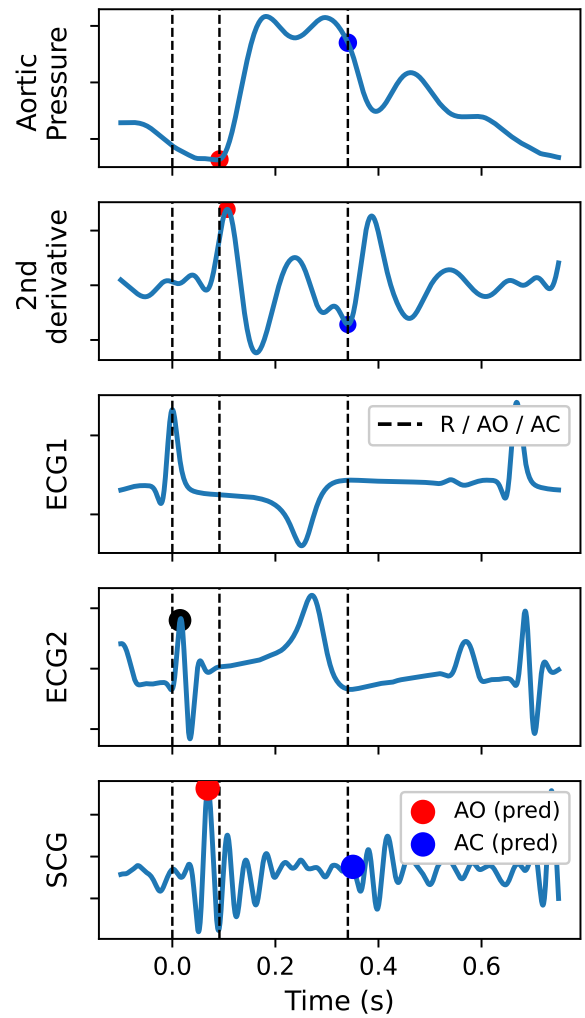


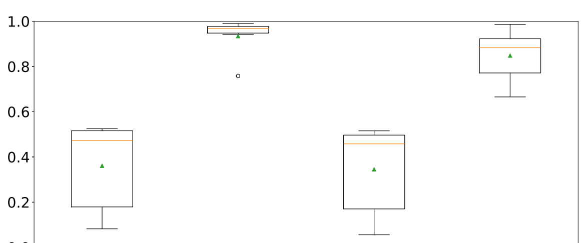
Figure 1: The method of identifying reference AO and AC from the aortic pressure.

2.3. Evaluation Criteria

The performance was evaluated in terms of detection performance and timing error. Detection performance was quantified using sensitivity and positive predictive value (PPV), computed on a beat-to-beat basis for each subject. For each pig, detected AO and AC events were matched to reference AO and AC events within ±50 ms, allowing calculation of true positives, false positives, and false negatives. A tolerance window of ±50 ms was used for event matching. Of this, approximately ±20 ms was considered clinically acceptable for timing accuracy. The remaining ±30 ms was included to account for uncertainty in the reference AO and AC, as they were derived from the R-peaks and aortic pressure signal rather than manually annotated with precise temporal markers. Therefore, based on the true positives, false positves, and false negatives the sensitivity and PPV was calculated for each pig. The median, interquartile range (IQR), mean, standard deviation (std), lower confidence interval (LCI), and upper confidence interval (UCI) of sensitivity and PPV were then calculated across all pigs for AO and AC individually. The timing error for all true positive detections was computed as the signed temporal difference between reference and SeismoTracker detected events. Based on this, the bias was calculated separately for AO and AC to obtain a global estimate of systematic temporal offset.

3. Results

6 pigs with a total number of 81983 individual heart beats (mean (std) of 13664 (3072)) were used in the study. For AO detection the PPV (IQR) was 0.968 (0.029) across all pigs, while for AC the PPV (IQR) was 0.883 (0.151). The median sensitivity (IQR) for AO was 0.473 (0.337) and 0.458 (0.326) for AC. All aggregated results from all the pigs are illustrated in figure 2. The mean (std) bias across all pigs was 1.48 (12.86) ms for AO and -11.57 (13.25). The mean bias for all pigs for AO was -24.5 ms ± 16.9 ms, while it was -0.91 ± 10.32 ms for AC.



	AO Sensitivity	AO PPV	AC Sensitivity	AC PPV
Median	0.473	0.968	0.458	0.883
IQR	0.337	0.029	0.326	0.151
Mean	0.361	0.934	0.345	0.848
Std	0.195	0.080	0.197	0.111
LCI	0.205	0.870	0.188	0.759
UCI	0.517	0.998	0.502	0.937

Figure 2: The AO and AC event sensitivity and PPV represented in box plots. The green triangle represents the mean. Morever, the median, interquartile range (IQR), mean, standard deviation (STD), lower confidence interval (LCI), and upper confidence interval (UCI) are presented.

4. Discussion

The algorithm achieved a high positive predictive value on the external dataset, indicating a low rate of false positive detections and reliable identification of AO and AC timings. This suggests that the method maintains robust performance in terms of detection specificity under independent conditions. However, the algorithm exhibited only a moderate sensitivity, reflecting a higher number of missed detections. While this trade-off reduces overall detection completeness, it remains acceptable given that the intended application prioritizes minimizing false positive detections. Moreover, even though SeismoTracker is conservative developed and not trained on pigs or hypovolemic cases, it still achieves very good PPV performance and moderate sensitivity performance, underlining the potential of the method. This also confirms that it is a conservative model. As an addition to this, the PPV and sensitivity obtained in the external validation set is similar to the results obtained from the original work [15], indicating generalizability and robustness of SeismoTracker for AO and AC detection. In addition, the algorithm is under further development to improve sensitivity without comprising the PPV, while also optimizing its performance in subjects with cardiac diseases.

The bias for AC at -11.57 indicates a slightly systematic detection error in the algorithm, which could be caused by different reasons. Firstly, during hypovolemia the stroke volume decreases due to the decrease in blood volume [18] resulting in a reduced ejection and thus a lower aterial pressure and flow. Furthermore, this results in less forceful AC which would manifest itself by softer and less distinctive S2. This is challenging for the algorithm and even a human annotator to identify due to the lack of distinct and consequent signal morphology that explains some of the AC detection error. Secondly, the exact timing of AC in the aortic pressure signal is also challenging to determine precisely, which also could result in detection error for SeismoTracker. Moreover, the exact AC timing in the SCG signal might also differ a bit [6, 16] across different definitions, which also could result in the systematic AC detection error.

Additionally, a large part of the dataset is recorded while the pigs have a blood loss volume (BLV) of up to 28%, which will change the morphology in the signal [16, 19], and the model has not been trained on either hypovolemic cases or pig data. This is some of the main reason for the detection errors resulting in the relatively low sensitivity. And especially including such different types of data in the training of a deep learning model is necessary to obtain good performance. However, the high PPV in the dataset emphasizes the potential of the model and its use in different datasets.

5. Conclusion

In conclusion, SeismoTracker demonstrated good overall performance in beat-to-beat AO and AC detection on the external dataset with a high PPV and moderate sensitivity indicating reliable detection supporting its generalizability and robustness to independent data.

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