Robustness of Persistence Diagrams to Time-Delay for Seismocardiogram Signal Quality Assessment*

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***Abstract*—Seismocardiography is a potent non-invasive cardiovascular monitoring technique whose widespread adoption is currently limited in ambulatory settings due to its susceptibility to corruption from environmental noise. In the absence of a clean concurrently collected electrocardiogram (ECG) signal as a heartbeat reference, template matching paired with windowing methods can serve as a useful method by which to assess seismocardiogram (SCG) signal quality. However, windowing methods can introduce a time-shift in the segmentation of the SCG beats as compared to a template due to persistently adapting heart rate. In this study, we assess the performance of a state-of-the-art SCG signal quality assessment algorithm, dynamic time feature matching (DTFM), in ranking SCG beats by signal-to-noise ratio when introducing an artificial time-delay. We compare this performance against that of a novel methodology based on topological data analysis (TDA) using persistence diagrams. We found no significant difference ($p>0.05$) in ranking performance between topological data analysis (TDA) and dynamic time feature matching (DTFM) when SCG beats were segmented by true R-peak locations. However, we found that TDA significantly outperformed DTFM ($p<0.001$) when SCG beats were segmented 100, 200, or 300 ms earlier than the R-peak locations. These results suggest the potential promise of TDA-based methods for robust ECG-free SCG signal quality analysis. These advancements may facilitate the analysis of longitudinal SCG data taken in out-of-clinic settings in situations where ECG monitoring is not viable.**

***Index Terms*—Topological Data Analysis, Persistence Diagram, Dynamic Time Feature Matching, Seismocardiogram, Signal Quality, Electrocardiogram-Free, Time-Delay Invariance**

I. Introduction

Seismocardiogram (SCG) derived features such as left ventricular ejection time, SCG magnitude, heart rate (HR) and HR variability (HRV) have demonstrable utility in the assessment of conditions such as heart failure and hypovolemia [1], [2]. However, despite its unique utility in non-invasive monitoring of cardiac mechanical function, the SCG is limited in ambulatory settings due to its susceptibility to environmental noise such as that induced by motion artifacts [3]. This can impact SCG preprocessing and the efficacy of feature extraction. Due to this susceptibility, a concurrently obtained electrocardiogram (ECG) trace is often used to localize the heartbeat and segment the SCG signal as part of preprocessing [4], [5]. However, reliance on ECG may not be feasible in scenarios where additional bulk, skin irritation, and sweat or body fluids limit its usability (e.g. military scenarios, neonatal care and trauma environments) [6], [7]. Thus, a major challenge is to reliably assess SCG signal quality without a reference ECG to enable the robust assessment of abnormal blood volume status or cardiac function in critical care settings.

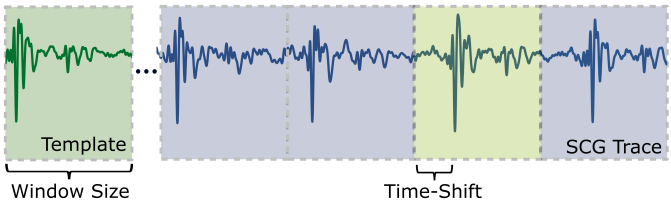

Fig. 1. Time-Shifts in Window-Based SQI Metrics: Window-based signal quality indexing can be performed by identifying a template beat and comparing to target SCG segments of the same window size. As the sliding window moves, varying amounts of time-shifts are introduced due to mismatch with heart rate, offsetting key SCG morphological features.

Time-domain approaches to assessing signal quality are advantageous as they may more directly reflect the quality of fiducial points on the SCG waveform which are used for feature extraction. Among these, template-matching algorithms are advantageous as they do not make any assumptions about the shape of a prototypical SCG beat which is unstandardized due to intrasubject variability [4]. Cross-correlation between a template waveform and the SCG trace can help to identify heartbeat locations [8]. However, direct correlation-based methods are limited as they do not account for stretching and compression of the SCG beat with changes in HR. Dynamic time warping (DTW) is robust to such deformations in time. However, the DTW algorithm aims to reduce Euclidean distance between a template and target beat without accounting for prominent features in the signal [4].

Dynamic Time Feature Matching (DTFM) addresses this issue by incorporating constraints on the warp path to account for important SCG fiducial points [4]. However, the algorithm's primary use-case is with ECG-segmented SCG beats. In the absence of an ECG, SCG segmentation may be performed by identifying repeatable signal features (e.g. the aortic opening location) [5]. However, this approach relies on the presence of clean features, defeating the purpose of signal

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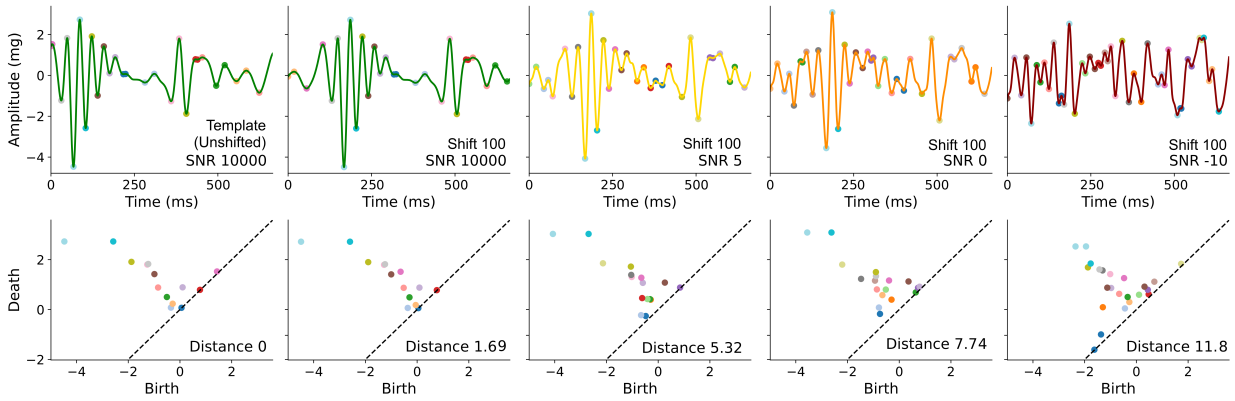

Fig. 2. Example seismocardiogram beat traces and corresponding persistence diagrams (PDs): We extracted PDs for the unshifted template beat and beats containing varying levels of added synthetic noise at multiple shift amounts. Beats of four SNR levels (10000, 5, 0, and -10) which were segmented 100 ms earlier than the ECG R-peak are shown above with decreasing SNR. Peaks and valleys are colored in accordance with their matching points on the PDs.

quality assessment. Another segmentation method is to utilize a sliding window across the SCG trace. However, the position of SCG beats within a window is not known a-priori. Thus, the beat can be misaligned from the template as shown in Figure 1. Assessing the difference in quality of a time-delayed target beat and a template may thus pose a challenge to state-of-the-art SCG SQI detection algorithms reliant on signal alignment.

Topological data analysis (TDA) may serve as a promising method to capture feature characteristics of the SCG waveform while overcoming the challenge of template alignment. Persistence diagrams (PD) are a powerful compact representation of waveform morphology and have been used successfully for mechanical biosignal analysis [9]. The extraction of PDs is invariant to smooth deformations in the signal such as skewing, stretching, rotations, and translations in time [10].

Thus, in this study, we analyze the effect of time-shifted segmentation of SCG beats on the ability of topological data analysis using persistence diagrams and DTFM to rank the signal-to-noise ratio of SCG beats. Such findings may help to inform the development of future ECG-free signal quality assessment algorithms. By enabling SCG signal quality assessment without the reliance on ECG, these algorithms can help to unlock the SCG's potential for longitudinal monitoring of cardiac mechanical function in ambulatory settings and critical care environments.

II. Methods

A. Experimental Protocol

This study uses a dataset described in detail in prior work by Zia et. al [2]. The protocol was approved by the Institutional Animal Care and Use Committees of the Georgia Institute of Technology, Translational Testing and Training Labs Inc. and the Department of the Navy Bureau of Medicine and Surgery. The data were collected from six anesthetized pigs who underwent an exsanguination procedure to induce hypovolemia at up to four different blood volume loss levels (7, 14, 21, and 28% of total blood volume or until cardiac collapse). Blood was refilled at the same increments, if possible, after exsanguination. A pause was taken for 5-10 minutes after reaching each blood volume loss level to allow the cardiovascular system to stabilize. In this study, data from one pig was discarded due to noise corruption. This is to ensure that the ground truth clean templates were reflective of optimal SCG signal quality. A BIOPAC MP160 data acquisition system was used to sample the electrocardiogram and seismocardiogram at 2 kHz throughout the protocol. An ADXL354 accelerometer (Analog Devices Inc., Norwood, Massachusetts, USA) was used to collect SCG signals at the mid-sternum.

B. Data Preprocessing

The data was first preprocessed by bandpass filtering the ECG and SCG signals with finite impulse response (FIR) band-pass filters with Kaiser windows. The cutoff frequencies were set to 0.5–30 Hz and 1–40 Hz for the ECG and SCG respectively. Filtering was performed in the forward and reverse directions to offset phase shift. Gaussian noise was added to the SCG signal at six signal-to-noise ratio (SNR) levels (10000, 10, 5, 0, -5, and -10 dB). These levels were chosen to match the SNR of SCG signals corrupted by vehicle vibrations, and calculated as $10log_{10}(MSP(signal)/MSP(noise))$, $MSP(s) = \sum(s^2)/length(s)$ [11]. For each pig, p, we used the Pan-Tompkin's algorithm to detect $N_p + 1$ R-peaks from the ECG signal corresponding to N_p heartbeats. Four levels of time-delay (shifts), s, in milliseconds were induced in the SCG beats $s = \{0, 100, 200, 300\}$. The beat was segmented according to the detected ECG R-peaks resulting in an unshifted beat ($s = 0$) or the start and end of beat segmentation was set to be earlier than the R-peak locations $s = 100, 200, 300$ resulting in a time-delayed beat. Every 50th beat was utilized for this analysis, and thus, for each pig and time-shift experiment, the processed dataset contained $M_p = \lfloor N_p/50 \rfloor$ observations $\{O_{1,s}, O_{2,s}...O_{M_p,s}\}$ of heartbeats. Each observation comprised of the original clean unshifted template beat, as

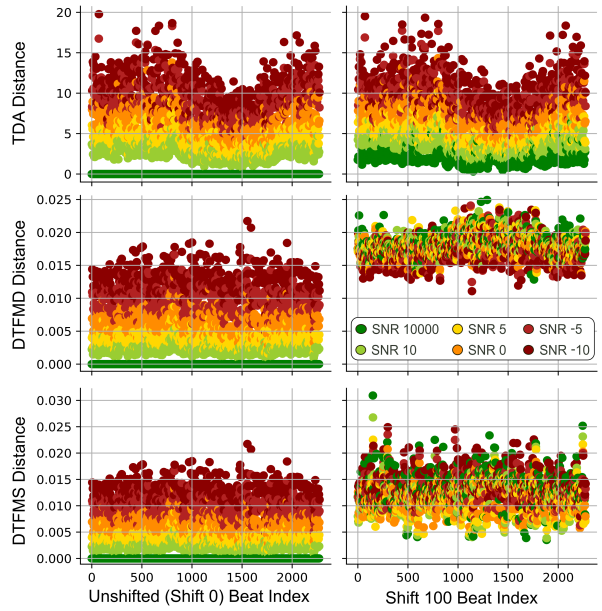

Fig. 3. Separability of SNR Levels Across Models: We used three models, Topological Data Analysis using Persistence Diagrams (TDA), Dynamic Time Feature Matching (DTFM) with Default Max Distance (DTFMD), and DTFM with Time-Shift Information Included (DTFMS) to quantify the difference between a reference unshifted clean template and noisy target beats segmented at varying shift amounts. TDA maintains robust separability in the unshifted and shifted cases while DTFM can only do so in the unshifted case.

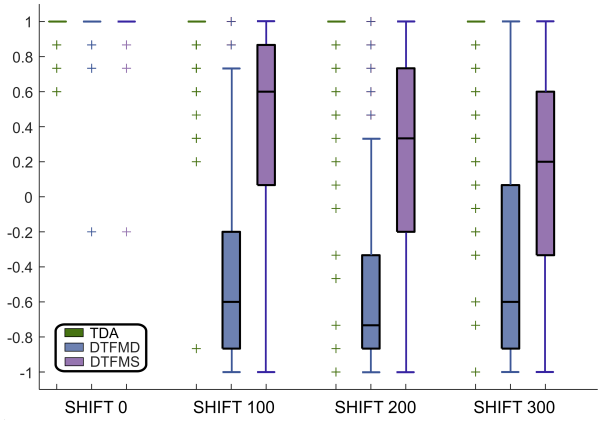

Fig. 4. Distributions of Kendall's tau values (ranging from 1: perfectly ranked to -1: oppositely ranked) for all beats per model and shift: Topological Data Analysis using Persistence Diagrams (TDA) does comparably to DTFMD and DTFMS when there is no time-delay. TDA ranking performance remains robust with time-delay while DTFM performance diminishes.

well as its time-shifted noisy correspondent beats (e.g., $O_{x,s} = \{O_{x,s,template}, O_{x,s,SNR_{10000}}, O_{x,s,SNR_{10}}, O_{x,s,SNR_5}, O_{x,s,SNR_0}, O_{x,s,SNR_{-5}}, O_{x,s,SNR_{-10}}\}$. Figure 2 illustrates an observation with a subset of the noise levels for clarity.

C. Model Descriptions and Ranking Task

A separate experiment was conducted at each time-shift condition to understand model ranking performance. For every shift level, s, three models were used to obtain a vector of distance values corresponding to beats of different SNR levels from observation $O_{x,s}|x \in [1, ..., M_p]$ and pig p. The first model employed topological data analysis using persistence diagrams. In this model, persistence diagrams were extracted via a sublevel set filtration procedure described in [9] from the clean unshifted template beat $O_{x,s,template}$ and each of the shifted noisy target beats $\{O_{x,s,SNR_{[10000,...,-10]}}\}$. The distance from each of these shifted noisy beats was determined by taking the Wasserstein distance between their persistence diagram and that of the template. The second model employed DTFM with the maximum distance between target and template beat features set to the default 50 ms (DTFMD). The third model utilized DTFM with the maximum distance set to the shift amount added to the default search distance (e.g., 200 ms shift + 50 ms default for a total maximum distance of 250 ms). This reasoning behind this design choice was to test DTFM performance when provided with a search window which overlaps with the true feature locations in the shifted noisy beat. The DTFM distance metric, defined as the minimum Euclidean distance between warped template and target signals after feature mapping, is described in detail by Zia et al [4].

D. Quantification of Performance

Kendall's Tau is a non-parametric correlation coefficient which measures the agreement in ordering between two sets of data. In this case, it measures each model's ability to order the beats in terms of decreasing SNR. For each possible pair of ranking values, the pair is concordant if the model's ranking is consistent with the ground truth and discordant if not. τ is then calculated as $\tau = (N_c - N_d)/(N_c + N_d)$ where N_c and N_d are the number of concordant and discordant pairs, respectively. $\tau = 1$ if the model's ranking is perfectly consistent with the ground truth and $\tau = -1$ if the ranking perfectly disagrees. $\tau = 0$ would result from no association or random ordering.

E. Statistical Testing

We used a generalized estimating equations (GEE) model to assess if there were significant differences in the performance of TDA, DTFMD, and DTFMS. We chose to use this nonparametric model as the Kendall's Tau distributions were nonnormal and the dataset contained repeated measures (beats) for each pig. After running the GEE model, we ran post-hoc pairwise comparisons with a Bonferroni correction (for 3 comparisons) to assess which pairs of models performed significantly differently. α was set to 0.05.

III. Results

Figure 3 illustrates the separability of the three models in the unshifted and 100 ms shift cases. Figure 4 illustrates the distribution of Kendall's Tau values for all models across each time-delay experiment, reflecting model ranking performance. The mean, μ, and standard deviation, σ of these distributions across models are additionally quantified in Table I and the Cohen's d effect size is given for each model pair in Table II.

In the case where SCG was not time delayed and segmented according to R-peak locations, all three models report mean

TABLE I
KENDALL'S TAU DISTRIBUTION STATISTICS PER MODEL AND SHIFT

	TDA		$DTFM_D$		$DTFM_S$	
	μ	σ	μ	σ	μ	σ
No Shift	0.993	0.036	0.998	0.036	0.998	0.036
100 ms Shift	0.981	0.088	-0.456	0.529	0.402	0.528
200 ms Shift	0.967	0.147	-0.570	0.478	0.199	0.576
300 ms Shift	0.942	0.194	-0.360	0.598	0.076	0.579

TABLE II
COHEN'S D EFFECT SIZE BETWEEN MODELS PER SHIFT

	No Shift	100 ms	200 ms	300 ms
TDA vs $DTFM_D$	-0.139	3.79	4.35	2.93
TDA vs $DTFM_S$	-0.139	1.53	1.82	2.01
$DTFM_D$ vs $DTFM_S$	0	-1.62	-1.45	-0.741

Kendall's Tau values above 0.99, with DTFM slightly outperforming TDA by 0.005. However, for the unshifted case, we found a significance level of p=0.075, indicating that this difference was not significant. For all shifted cases (100, 200, and 300 ms), p<0.001 and post-hoc analyses showed significant differences between all pairs of models. For the 100 and 200 ms shifts, p<0.001 for all pairwise comparisons and for the 300 ms shift, p<0.001 between TDA and DTFMD and TDA and DTFMS and p=0.008 between DTFMD and DTFMS. For all shifted cases, the performance of TDA remains above 0.94 while DTFMD and DTFMS performance sharply diminishes. DTFMS performance decreases to approximately 0-0.4, while DTFMD performance becomes negative (μ<0).

IV. DISCUSSION AND CONCLUSION

When an ECG can be concurrently collected with the SCG signal, SCG beats can be segmented according to the ECG R-peaks such that the resultant beats are roughly aligned in terms of cardiac cycle. From the results from the experiment with 0 ms (unshifted) time-delay, we demonstrate that TDA can rank beats according to SNR level at a comparable quality to state-of-the-art DTFM. In the case where beats are offset in time from the cardiac cycle by 100, 200 or 300 ms, TDA remains robust in its capability to discriminate between SCG beats of different SNR levels while DTFM performance drops. DTFMS performance stays positive but diminishes from the unshifted case likely due incorrect mappings to extra spurious candidate points introduced by noise. DTFMD ranks inversely to SNR (negative μ), likely due to the inability of the model to find any candidate points to match to in clean shifted signals when the corresponding feature is out of range, but the ability to find a match, though incorrect, when spurious peaks and valleys are introduced by noise. This discrepancy demonstrates the dependency of the DTFM model performance on intelligently chosen hyperparameters. TDA does not require fine-tuning thus decreasing the burden on the user.

The study contains limitations. The ranking of beats by SNR levels was performed with a perfect template, the ground truth unshifted clean versions of those same beats, to assess differences in model performance solely based on time-shift. Future work should assess model performances with global templates and assess the causes behind failure points. Additionally, the models were assessed in data from porcine subjects but should be evaluated with data from larger datasets with human subjects as well. Future work should also assess model performance in different environmental scenarios with motion artifacts and physiological rather than Gaussian noise.

In this work, we demonstrated the robustness of topological data analysis using persistence diagrams to time-delays in beat segmentation when performing SCG signal quality analysis. Through this validation, the study takes a stride towards understanding the limitations of current state-of-the-art signal quality assessment techniques and towards the development of robust ECG-free SCG signal quality analysis methodologies. Such an advancement may enable the monitoring of cardiac mechanical function in out-of-clinic or critical care settings where noise is prevalent and wearable sensing hardware must be optimized for lightweight, longitudinal monitoring.

V. DISCLOSURE

O. T. Inan is co-founder of Cardiosense, Inc., and holds equity interest in the company.

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