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.

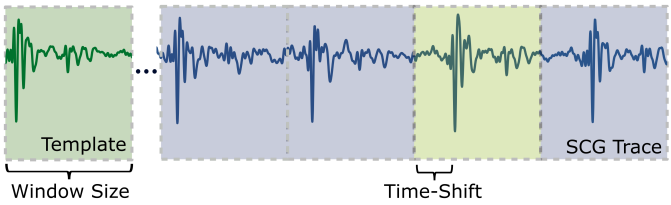

Fig. 1. Time-Shifts in Window-Based SQI Metrics: Window-based signal quality indexing can be performed by identifying a template beat and comparing to target SCG segments of the same window size. As the sliding window moves, varying amounts of time-shifts are introduced due to mismatch with heart rate,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

This work was supported by the Office of Naval Research (ONR) under Grants N000141812579, N000142112036, and N000142512219. The work of A. Nawar was additionally supported by the Clare Boothe Luce Fellowship and the National Science Foundation Graduate Research Fellowship (NSF GRF, DGE-2039655).

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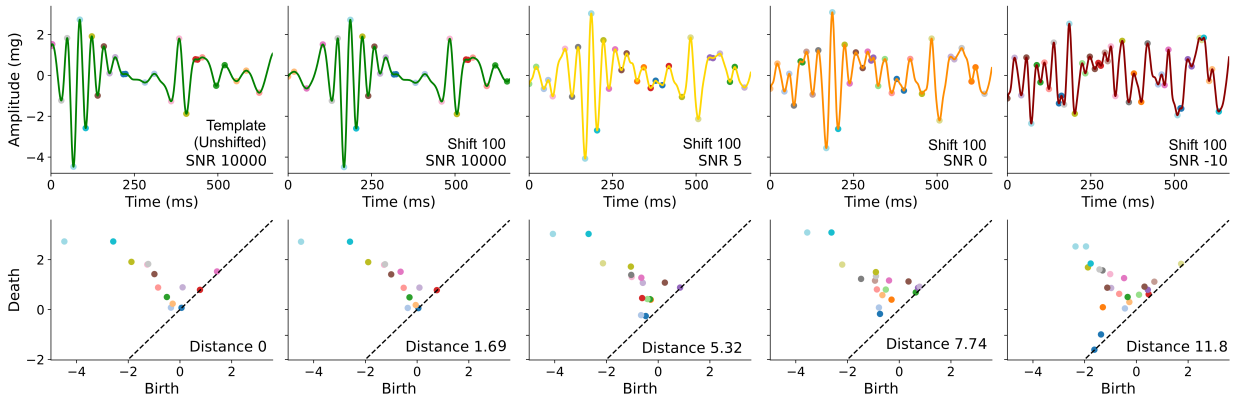

Fig. 2. Example seismocardiogram beat traces and corresponding persistence diagrams (PDs): We extracted PDs for the unshifted template beat and beats containing varying levels of added synthetic noise at multiple shift amounts. Beats of four SNR levels (10000, 5, 0, and -10) which were segmented 100 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

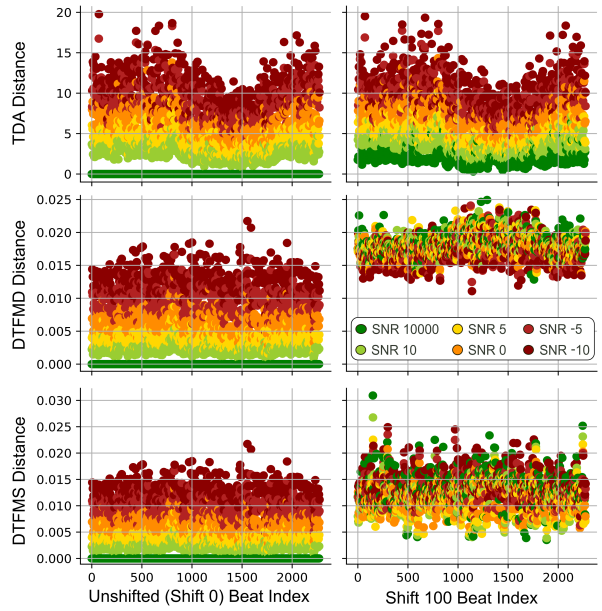

Fig. 3. Separability of SNR Levels Across Models: We used three models, Topological Data Analysis using Persistence Diagrams (TDA), Dynamic Time Feature Matching (DTFM) with Default Max Distance (DTFMD), and DTFM with Time-Shift Information Included (DTFMS) to quantify the difference between a reference 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.

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].

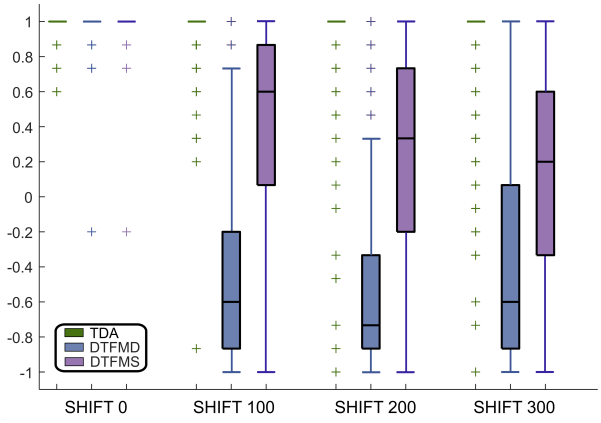

Fig. 4. Distributions of Kendall's tau values (ranging from 1: perfectly ranked to -1: oppositely ranked) for all beats per model and shift: Topological Data Analysis using Persistence Diagrams (TDA) does comparably to DTFMD and DTFMS when there is no time-delay. TDA ranking performance remains robust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

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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BSN-2025 – "Time-Delay Invariance of Persistence Diagrams for Seismocardiogram Signal Quality Assessment"

Dear Program Chairs and Reviewers,

Thank you for taking the time to carefully review our manuscript and provide us with detailed and informative comments. We have responded to each of the comments below in a point-by-point fashion and have included sections for the new/modified text in the revised manuscript if applicable. The revisions are documented below, with responses noted in **Blue**, cited portions listed in **Green**, and changes highlighted in yellow. These revisions have enabled us to greatly strengthen the paper and we believe we have addressed all comments to the best of our ability.

We look forward to hearing your feedback on our revised manuscript.

Sincerely,

Afra Nawar (on behalf all the authors)

Response to the Reviewer's comments to the authors:

Reviewer 1:

Summary Of The Paper:

This study assessed the performance of an algorithm, dynamic time feature matching (DTFM), in ranking SCG beats by signal-to-noise ratio when introducing an artificial time-delay. This method was compared with a methodology based on topological data analysis (TDA) using persistence diagrams. The results showed no significant difference in ranking performance between TDA and DTFM when SCG beats were segmented by true R-peak locations. However, TDA significantly outperformed DTFM when SCG beats were segmented 100, 200, or 300 ms earlier than the R-peak locations.

We thank the reviewer for thoroughly reading through our paper to find areas of strengths and weaknesses. We believe we have addressed each comment on a point-by-point basis which we have described below:

Strengths:

The main contribution of the this study is to evaluate the quality of SCG signals with different delay with respect to the R-peak location.

We thank the reviewer for assessing the paper's merits noting the ability of the proposed TDA-based SCG SQI algorithm to adequately assess the quality of the beats even with different delay amounts.

Weaknesses:

1. **Novelty is limited. Both algorithms (DTFM and TDA) have been published in previous studies.**

   We thank the reviewers for their comment. We agree that DTFM and TDA are both well documented algorithms which have use cases in many domains. However, we believe that this does not preclude the novelty of the paper. SCG-derived features have shown demonstrable utility towards the assessment of conditions such as heart failure and hypovolemia [1, 2]. However, the SCG can be heavily affected by motion artifacts and noise which can affect the efficacy of feature extraction [3]. Because such noise is ubiquitous in real-world scenarios, there is a critical need for the application of novel algorithms for SCG signal quality detection to ensure the validity of the extracted feature set. Thus, rather than taking away from the impact of the paper, we believe that the validated usage of these algorithms in prior work with time-series signals *adds credence* to the work as it enables us to be more confident in their application to SCG signal quality analysis.

   To improve the clarity of the novelty of the paper, we have reframed part of the introduction to better describe the impact of SCG signal quality assessment such that

the importance of SQI assessment to enable robust SCG preprocessing and feature extraction is understood:

"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 [~], [~]. Despite its unique utility in non-invasive monitoring of cardiac mechanical function, the SCG is susceptible to environmental noise such as that induced by motion artifacts, especially in ambulatory settings [~]. 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 [~], [~]. 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) [~], [~]. 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." – Section I

2. **Working principles of DTFM and TDA are missing. Although they have been previous published, some detailed description rather than a reference can help the readers for better understanding.**

We thank the reviewers for their request for additional description about the methodology for DTFM and TDA. We agree that an expanded explanation of the algorithms could aid in understanding their application in this domain. Because of this request we have clarified some of the methodological details for each algorithm as shown below in Section II: Methodology, Part C Model Descriptions and Ranking Task.

To the TDA description, we add in information about the filtration methodology that is used to convert the time-series signal to the persistence diagram.

"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 [~] from the clean unshifted template beat Ox,s,template and each of the shifted noisy target beats {Ox,s,SN R[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." – Section II, Part C

We also add additional information describing the DTFM distance metric:

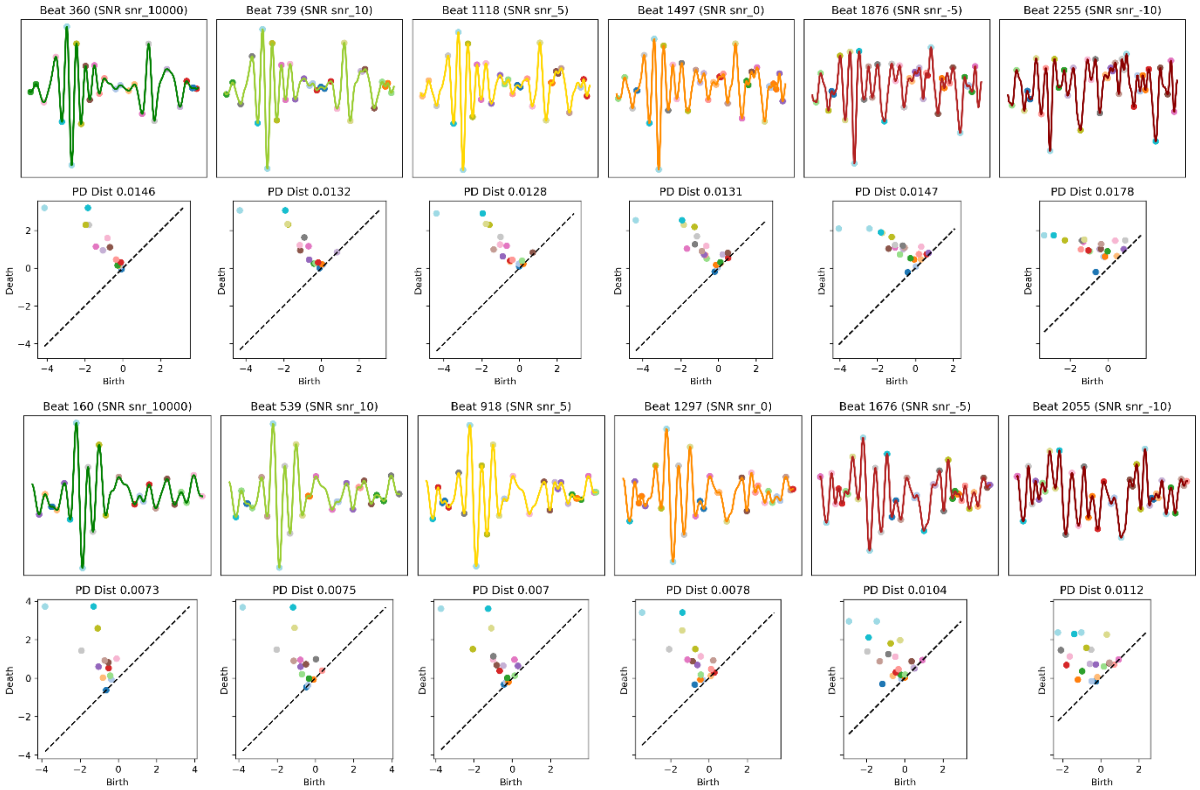
"This reasoning behind this design choice was to test DTFM performance when provided with a search window which overlaps with the true feature locations in the shifted noisy beat. The DTFM distance metric, defined as the minimum Euclidean distance between warped template and target signals after feature mapping, is described in detail by Zia et al [~]." – Section II, Part C

3. **In Fig. 2, it is weird that there is no significant difference between the signals with SNR of 10000 and -10 dB.**

We thank the reviewer for their curiosity on the differences between the visual characteristics of beats with 10000 dB and -10 dB SNR. The SNR of the signal was calculated using taking the log of the mean squared power of the signal to noise. The formula is given below:

$$dB = 10\log_{10}\left(\frac{\sum\frac{signal^2}{len(signal)}}{\sum\left(\frac{noise^2}{len(noise)}\right)}\right)$$

Additional examples of beats are provided here for reference to show how the -10 dB and 10000 dB cases can appear quite different from the initial signal:



We also add in the following verbiage to make the calculation of the SNR levels more clear:

"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 10log10(MSP (signal)/MSP (noise)), MSP(s) = P(s^2)/length(s) [11]. For each pig, p, we used the Pan-Tompkin's algorithm to detect Np + 1 R-peaks from the ECG signal corresponding to Np heartbeats. Four levels of time-delay (shifts), s, in milliseconds were induced in the SCG beats s = {0, 100, 200, 300}." – Section II, Part B

4. **The choice of SNR levels, i.e., 10000, 10, 5, 0, -5, and -10 dB, is also a bit weird. Why these levels and how are they agree with realistic?**

We appreciate the reviewer's curiosity about the choice of the noise levels in the study. We based the choice of these levels on prior work in SCG signal quality analysis with the application of artificial noise [4]. The lower SNR limit was chosen to match the SNR of aortic opening and closing complexes when corrupted by real world subway vibrations [4]. We thus utilize these levels as they are validated in prior work and likely representative of the level of noise in real-world conditions in which the algorithm should be deployed.

To make this reasoning clearer, we have added additional description on the SNR levels in Section II Methodology, Part B Data Preprocessing:

"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 10log10(MSP (signal)/MSP (noise)), MSP (s) = P(s2)/length(s) [~]. For each pig, p, we used the Pan-Tompkin's algorithm to detect Np + 1 R-peaks from the ECG signal corresponding to Np heartbeats. Four levels of time-delay (shifts), s, in milliseconds were induced in the SCG beats s = {0, 100, 200, 300}." – Section II, Part B

5. **Abbreviations should and only be explained in the first appearance.**

We thank the reviewer for their feedback regarding the explanation of abbreviations in the paper. Based on this comment, we have changed the following sections to ensure that abbreviated concepts are explained on first appearance (however, as a note -

because abstracts are generally expected to be self-contained, any abbreviations noted in this section are not counted as first appearance).

"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." – Section I, Paragraph 1

"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 particularly powerful as a compact representation of waveform morphology and have been used successfully in prior work for mechanical biosignal analysis [~]. The extraction of PDs is invariant to smooth deformations in the signal including scaling differences (such as amplitude variations) and translations (such as time-shift delays) [~]." – Section I, Paragraph 4

Reviewer 2:

Summary Of The Paper:

This manuscript presents a comparative study of a TDA-based approach versus DTFM for signal quality assessment of SCG signals under time-delay perturbations. The authors evaluated beat ranking performance across noise levels using PDs and quantified it with Kendall's Tau correlation, to argue that the TDA method is robust to temporal misalignment in SCG segmentation as compared to previous methods. The study is very relevant for ECG-free SCG assessment in ambulatory scenarios.

We thank the reviewer for thoroughly reading through the manuscript and for noting its potential utility for SCG signal quality assessment especially in ambulatory scenarios and scenarios ECG may not be feasible to use. We believe that we have addressed all of the comments and give our responses below in a point-by-point manner.

Strengths:

The introduction is particularly well-written: it clearly lays out the problem of ECG-dependent SCG quality assessment and motivates the need for ECG-free methods in settings like ambulatory monitoring or critical care.

We thank the reviewer for this comment and appreciate the recognition of the importance of the problem of ECG-dependent SCG signal quality assessment. We agree with the reviewer that developing new methods for SQI assessment which are not reliant on the ECG can enable more robust monitoring of suboptimal cardiovascular function (e.g. in the case of hemorrhage and hypovolemia) when ECG usage is infeasible. Thus, we are pleased to hear that the problem statement is clear.

The authors effectively frame why time-delay robustness matters and why TDA might be a viable solution.

We thank the reviewer for their comment. We are pleased to hear that the reasoning behind using topological data analysis to address the problem of ECG-dependent SCG signal quality indexing is clear.

The authors transparently discuss the limitations of their setup (e.g., reliance on clean templates and porcine data) and propose meaningful next steps.

We thank the reviewer for their comment. Indeed, in addition to the analysis presented in this manuscript, we recognize that there are many promising areas of future work which are important towards continuing to develop robust ECG-free SCG SQI assessment algorithms. We are pleased to hear that these areas of development are clear and that our transparency is appreciated.

The study design, particularly the controlled addition of noise across a range of SNR levels and the systematic evaluation of time-delay offsets, allows for a clean comparison between DTFM and TDA.

We thank the reviewer for this comment. Indeed, many of the study design choices were made such that the differences between the algorithms and the effect of time-delay could be clearly understood. We, thus, greatly appreciate the reviewer's recognition of the thought behind our study design.

Weaknesses:

1. **As the authors note, the study is based on SCG from anesthetized pigs in a controlled hemorrhage model. While this present work is still useful as a proof-of-concept, the absence of validation on human data, especially in ambulatory, wearable use cases where motion artifacts and inter-subject variability are much more severe, as discussed by the authors in the introduction, limits the practical impact of the findings. Future work should aim to include human SCG recordings under realistic conditions.**

   We thank the reviewer for pointing out limitations in the dataset composition. The reviewer is correct that the choice of the dataset is useful as a proof of concept but we also believe that the choice of dataset is also directly relevant to real-world applications

of SCG signal quality. In this study, we chose to use an anesthetized porcine population as this population allowed us to understand the robustness of SCG signal quality from healthy cardiac function as well as multiple suboptimal blood volume states due to hypovolemia. These signals are difficult to obtain in a controlled manner from a human population, but such conditions affect the underlying SCG signal characteristics [1,2,4]. It is, thus, important that signal quality indices are robust to varying SCG morphology from different cardiovascular states as SCG features have demonstrable utility for the assessment of suboptimal cardiovascular function in many critical care scenarios where hypovolemia may be present [1,2].

Although we believe that using such a dataset allows us to better understand algorithm behavior under suboptimal cardiovascular function than a human dataset, we agree with the reviewer and recognize that there are many sources of variability in real world situations which marks the importance of eventually assessing model performance with other datasets with larger sample sizes, motion artifacts, and human data.

We thus modify Section IV: Discussion and Conclusion to highlight the necessity of larger datasets of human data following up with our discussion on adding more realistic sources of noise as areas of future research:

"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 physiological rather than Gaussian noise." – Section I: Introduction

2. The manuscript mentioned post-hoc Bonferroni, but it would be better to provide more parameter details of the Bonferroni test, such as the effect size.

We thank the reviewer for their request for additional clarity on the Bonferroni correction applied to the statistical testing. The number of comparisons that were corrected for was 3 and thus, the corrected α=0.05/3=0.017. We have added additional information about the test as shown below to Section II Methods, Part E: Statistical Testing:

"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. All significance levels were set at $\alpha = 0.05$." – Section II

Additionally, we have added an additional table – Table II: Cohen's D Effect Size Between Models Per Shift quantifying the effect size of each group comparison in each shift case:

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

Finally, we update the wording of Section III: Results to refer the readers to this table:

"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." – Section III

3. **The title and abstract refer to TDA as "time-delay invariant." However, persistence diagrams are not strictly invariant to arbitrary time shifts, especially in discrete signals or when no embedding is applied. They are stable under certain types of signal perturbations, but without a clear explanation of the filtration used, the claim of invariance is a bit overstated.**

We thank the reviewer for their comment regarding the invariance of persistence diagrams to time delays. Although TDA is invariant to smooth deformations of the signal when the signal value set remains the same, the reviewer is correct that segmentation of the SCG signals at slightly different time points will change the input signal which may cause differences in the output persistence diagram. Thus, we believe that a better term to describe the effectiveness of TDA for SCG signal quality in the case of time-delays may be "robustness" rather than "invariance" to avoid the misinterpretation that there are no changes at all to the extracted persistence diagram representation. To ensure the clarity of our methods and to avoid confusion, we have made several changes to the paper as shown below.

First, as suggested by the reviewer, we add greater description of the filtration method used for the time series signals in Section II Methods, Part C: Model Descriptions and Ranking Task:

"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 Ox,s,template and each of the shifted noisy target beats {Ox,s,SN R[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." – Section II, Part C

We change the title to better reflect the "robustness" rather than "invariance" of the method:

"Robustness of Persistence Diagrams to Time-Delay for Seismocardiogram Signal Quality Assessment" – Title

Finally, we rephrase the following wording to be more precise:

"Persistence diagrams (PD) are particularly powerful as a compact representation of waveform morphology and have been used successfully in prior work for mechanical biosignal analysis [~]. The extraction of PDs is invariant to smooth deformations in the signal such as skewing, stretching, rotations, and translations in time [~]." – Section I

4. **Just some minor typos: Figure 4 caption: "Analaysis". Second-to-last paragraph of Discussion: "Addiitonally".**

We thank the reviewer for noting the typographical errors that have occured in our manuscript. We have taken time to proofread the paper again and we have fixed these errors in the manuscript by rewriting the text or fixing the spelling mistakes as shown below:

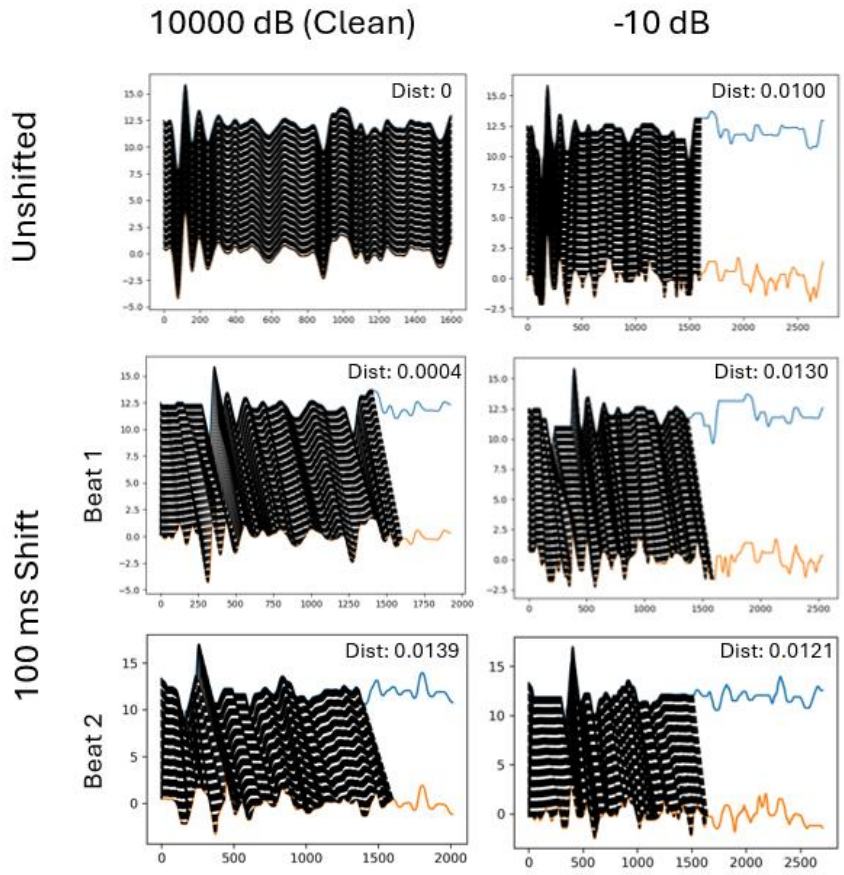
"Four levels of time-delay (shifts), s, in milliseconds were induced in the SCG beats s = {0, 100, 200, 300}. The beat was segmented according to the detected ECG R-peaks resulting in an unshifted beat (s = 0) or the start and end of beat segmentation was set to be earlier than the R-peak locations s = 100, 200, 300 resulting in a time-delayed beat." - Section II Methods, B: Data Preprocessing

"Future work should assess model performances with global templates. Additionally, the models were assessed in data from porcine subjects but should be evaluated with data from human subjects as well." - Section IV Discussion and Conclusion

"The above figure depicts the 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." - Figure 4 Caption

5. **“DTFMS performance stays positive but diminishes from the unshifted case likely due (to) incorrect mappings to extra spurious candidate points introduced by noise. ” This explanation remains speculative, and it would be great, in future work, for a quantitative analysis of the failure cases. Is there a systematic pattern in how noise disrupts the performance, e.g. valleys/peaks? Any insight here would add clarity to the observed performance drop.**

We thank the reviewer for their curiosity about the reduced performance of the DTFMS algorithm. We completely agree that each method’s failure points should be assessed in greater detail in future work. Because of this, we have plotted an example waveform to form an initial backing for our statement about DTFMS performance as shown below:



From the above images, we can see that for the unshifted case, the major peaks are mapped correctly between template and target. However, with even a 100 ms shift, the mapping becomes more inconsistent between template and target (which can result in inconsistent ordering of distance metrics across SNR levels).

As these are exploratory analyses, we have modified Section IV: Discussion and Conclusion, to highlight this area of future work:

"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 human subjects as well." – Section IV

Reviewer 3:

Summary Of The Paper:

This paper evaluates the possibility of topological data analysis (TDA) with persistence diagrams for assessing signal quality in seismocardiogram (SCG) signals with no ECG reference. The study shows that TDA has comparable performance with dynamic time feature matching (DTFM) when segments are taken perfectly, and performs better than DTFM when the segment is taken with a shift from R-peaks. Such a result facilitates TDA as a robust method for SCG quality evaluation.

We thank the reviewer for reading through the manuscript and noting areas of strength and areas for improvement or clarification. We have addressed each comment below on a point-by-point basis.

Strengths:

This research provides an alternative solution for the problem of SCG quality assessment, which is challenging when no other bio signals can serve as references.

We thank the reviewer for noting the potential for TDA to help address the problem of SCG signal quality assessment without a reference signal. Indeed, we agree that the problem is challenging because of the loss of complementary information (i.e. a sense of periodicity from the ECG) which is useful for SCG preprocessing. However, we agree that TDA can help to extract morphological information from the signal which can enable robust SCG SQI analysis.

This research investigates the performance of quality assessment methods under the case when SCG is segmented with a shift from R-peaks, which can happen with no references or clean features. Such an investigation is beneficial for the clinical use of SCG.

We thank the reviewer for noting the potential impact area of ECG-free SCG signal quality analysis. Indeed, we agree that developing SCG SQI methods which are robust to slight misalignments in SCG preprocessing are critical towards enabling robust SCG usage in scenarios

of suboptimal cardiovascular function especially in scenarios where noise artifacts may be prevalent. Thus, we appreciate the reviewer's recognition of the impact of our manuscript.

Weaknesses:

This research is evaluated on data from 5 pigs. This weakens the soundness of the result in multiple ways. First, the scale of data and the number of subjects are small, bringing large randomness and little inter-subject differences. Second, with plenty of relevant works evaluated on SCG from humans, it does not make sense for the authors to use the data from pigs, assuming that they aim to promote the use of SCG in human clinical applications. Third, the subjects are set to have a large variation in blood volume loss levels. Why is such a factor important for SCG quality assessment? Is it closely related to the potential application of SCG? Such a setup does not seem common in previous relevant works.

We thank the reviewer for their concern about the characteristics of the dataset population. The reviewer is correct that the choice of the dataset is directly applicable to the potential impact area of the work. In this study, we chose to use an anesthetized porcine population as this population allowed us to understand the robustness of SCG signal quality from healthy cardiac function as well as multiple suboptimal blood volume states due to hypovolemia. These signals are difficult to obtain in a controlled manner from a human population, but such conditions affect the underlying SCG signal characteristics [1, 2, 4]. It is, thus, important that signal quality indices are robust to varying SCG morphology from different cardiovascular states as prior work has shown that SCG features have demonstrable utility for the assessment of suboptimal cardiovascular function in many critical care scenarios where hypovolemia may be present [1,2].

Thus, we believe that using such a dataset allows us to feasibly assess algorithm behavior under suboptimal cardiovascular function that would be difficult to collect with a human dataset [4]. Nonetheless, we recognize the importance of eventually assessing model performance with other datasets with larger sample sizes, including human SCG.

We thus modify Section IV: Discussion and Conclusion to highlight the need to validate these approaches in larger datasets of signals derived from human subjects:

"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 physiological rather than Gaussian noise." – Section I: Introduction

For the evaluation of SCG quality assessment capability, the authors apply Gaussian noise to the clean data to imitate data of low quality. However, common noises in SCG, including motion artifacts, have distinct features from Gaussian noise. Results from the paper fail to represent the method's performance on real collected SCG data.

We thank the reviewer for their concern about the type of noise added to the clean SCG signals in this study. In physiological signals, it is often difficult to assess realistic noise characteristics independently from the cardiac signal because realistic noise can overlap with the frequency content of the true signal [5, 6]. Disentangling this noise from the true physiological signal is currently an area of ongoing research [5, 7]. In this study, our main aim was to assess how well each algorithm could assess signal quality given ground truth labels for signal quality (the dB levels). We, thus, decided against using physiologically grounded noises in this initial study, such that we can assess the performance of the algorithms without needing to quantify how much of the "noise" signal may contain true cardiac information. More simply, this methodology allowed us additional control over the signal perturbation process to quantify algorithm performance.

However, we still agree with the reviewer that future work should continue to assess the performance of the methodology with other types of noise as SCG SQI algorithms will eventually be used with real world scenarios. Because of this, we have modified the wording of Section IV: Discussion and Conclusion to highlight this area of future research as shown below:

"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." – Section IV

This work is a comparative study with overstated novelty. TDA has previously been applied to biomedical time-series classification tasks. Applying it to SCG quality assessment is meaningful but not completely novel. Together with the problem in experiment data and evaluation methods, this makes the overall contribution of this paper relatively low.

We thank the reviewers for their comment. We agree that TDA is a well-documented field which can have use cases in many domains. However, this does not preclude the novelty of the paper as there are still prevalent gaps in the performance of current methods for the robust assessment of SCG SQI quality which is the main goal of the study. Thus, rather than taking away from the impact of the paper, we believe that the validated usage of these algorithms in prior work with time-series signals *adds credence* to the work as it enables us to be confident in their application to SCG signal quality analysis.

We thank the reviewers for their comment. We agree that TDA is a well-documented field which can have use cases in many domains. However, we believe that this does not preclude the novelty of the paper. SCG-derived features have shown demonstrable utility towards the assessment of conditions such as heart failure and hypovolemia [1, 2]. However, the SCG can be heavily affected by motion artifacts and noise which can affect the efficacy of feature extraction [3]. Because such noise is ubiquitous in real-world scenarios, there is a critical need for the application of novel algorithms for SCG signal quality detection to ensure the validity of the extracted feature set. Thus, rather than taking away from the impact of the paper, we believe that the validated usage of these algorithms in prior work with time-series signals *adds credence* to the work as it enables us to be more confident in their application to SCG signal quality analysis.

To improve the clarity of the novelty of the paper, we have reframed part of the introduction to better describe the impact of SCG signal quality assessment such that the importance of SQI assessment to enable robust SCG preprocessing and feature extraction is understood:

"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 [~], [~]. Despite its unique utility in non-invasive monitoring of cardiac mechanical function, the SCG is susceptible to environmental noise such as that induced by motion artifacts, especially in ambulatory settings [~]. 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 [~], [~]. 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) [~], [~]. 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." – Section I: Introduction

Expression and spelling errors occur in this paper, like "Either... Otherwise..." in Section II B and "Addiitonally" in the second paragraph of Section IV. Another proofreading may be beneficial.

We thank the reviewer for noting the typographical errors that have occured in our manuscript. We have taken time to proofread the paper again and we have fixed these errors in the manuscript by rewriting the text or fixing the spelling mistakes as shown below:

"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.” - Section II Methods, B: Data Preprocessing

“Future work should assess model performances with global templates. Additionally, the models were assessed in data from porcine subjects but should be evaluated with data from human subjects as well.” - Section IV Discussion and Conclusion

“The above figure depicts the 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.” - Figure 4 Caption

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