Uncertainty Quantification of Cardiac Position on Deep Graph Network ECGI

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Abstract

Subject-specific geometry such as cardiac position and torso size plays an important role in electrocardiographic imaging (ECGI). Previously, we introduced a graph-based neural network (GNN) that is dependent on patient-specific geometry to improve reconstruction accuracy. However, geometric uncertainty, including changes in cardiac position and torso size, has not been addressed in network-based methods. In this study, we estimate geometrical uncertainty on GNN by applying uncertainty quantification with polynomial chaos emulators (PCE). To estimate the effect of geometric variation from common motions, we evaluated the model on samples generated by different heart torso geometries. The experiments shows that the GNN is less sensitive to heart position and torso shape and helps us direct development of similar models to account of possible variability.

1. Introduction

ECGI [1] aims to reconstruct cardiac electrical sources from high density ECGs or body surface potentials (BSPs) mathematically. Classic ECGI methods incorporate physical models based on patient specific medical imaging as prior knowledge [1–4]. ECGI can be used to diagnose and treat cardiac Arrhythmias, but its expansion into clinics has been hampered by inaccuracies, some of which may derive from geometric error of the model.

Previously, we introduced a graph-based neural network (GNN) [5] that reconstructs non-Euclidean image sequences by directly learning the inverse mapping as a function of the underlying geometry as shown in Fig. 1. The goal of this GNN approach form a mathematical approach to the ECGI that is less sensitive to variations in geometry and that is numerically better posed than traditional ECGI. However, since patient geometry is still used to train the model, our new approach may also be sensitive to geometric errors.

The patient-specific geometry plays a critical role in the physics-informed prior knowledge in bioelectric simulation, including ECGI. Geometrical uncertainty in patients can result from changes in patient posture and respiratory cycle, altering the cardiac positions and torso size, which can subsequetly impact ECG signal simulation and the resulting inverse solutions [6,7]. While the sensitivity to geometric error is difficult to determine experimentally, uncertainty quantification (UQ) methods can be used to systematically explore model sensitivity to these errors to better understand their accuracy and ways to improve them.

In this paper, we applied uncertainty quantification to the GNN to estimate model uncertainty due to torso and cardiac geometry. Using polynomial chaos emulators (PCE) and efficient sampling of the parameterized geometric variation, we were able to estimate the expected variation of a nominally trained GNN-ECGI model. For comparison, we performed similar UQ on a classic tikhonov ECGI model. Our goal in this study was to determine the sensitivity of the GNN-ECGI pipeline to cardiac position and torso shape in relation to more classical ECGI approaches. This work highlights the sensitivity of the trained GNN to heart position and torso size and helps us direct development of similar models to account of possible variability.

2. Methodology

Graph-based Neural Network We use graphs to represent the triangular meshes of both torso and heart, where the patient-specific geometry is presented by the topology of vertices and edges. The hierarchical geometry preserves the patient-specific information and embeds both torso and heart domain in a lower dimension representation.

To describe the propagation of signals on each domain, we define both encoder and decoder over geometric space by using spatial-temporal graph neural networks, which has interlaced graph CNN in space and regular convolution in time.

We then define the inverse mapping as a function of geometry. Specifically, the potential on one site on torso can be represented as a combination of the potential from all nodes on heart, where the coefficients are determined by the relative distance between heart and torso. We assume the linearity to hold in the latent space and explicitly model

 ISSN: 2325-887X DOI: 10.22489/CinC.2022.425

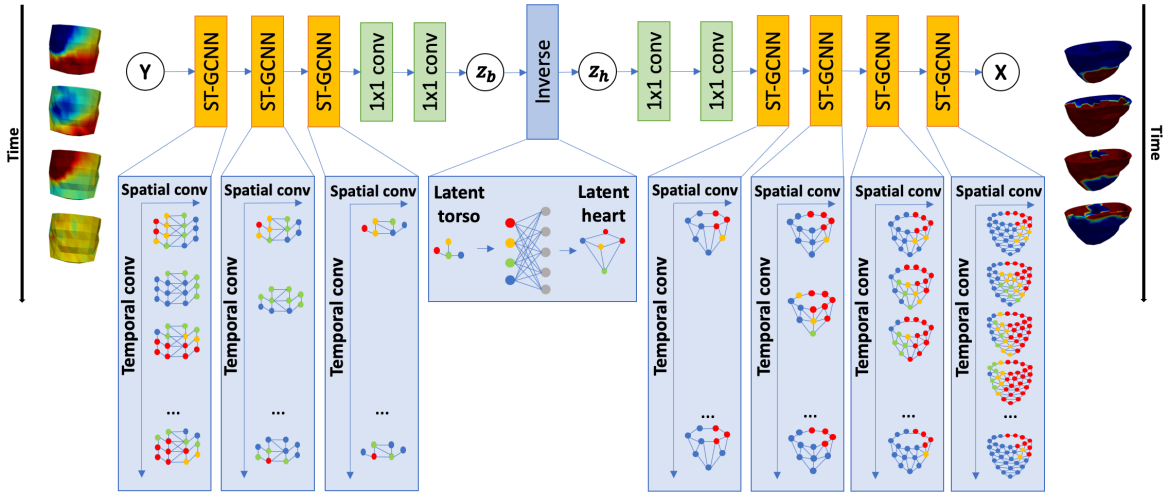

Figure 1. Overview of the graph-based neural network [5].

the inverse mapping as a linear function where the coefficients are function over geometry.

The GNN was trained using multiple recorded beats (800 beats) and the nominal geometry obtained from a torso tank experiment including tank and pericardial sock electrodes (Sec. refsec:experiments).

Tikhonov Regularization Classical ECGI was performed using zero-order Tikhonov Regularization [2] as a comparison for the GNN-ECGI. We used the tikhonov regularization implemented in SCIRun [8] using the L-curve method to find the regularization parameter. The full cardiac cycle was regularized in a block and the regularization parameter was chosen for each beat and geometry.

Experiments We obtain *in-vivo* recordings from an animal model experiment [9]. Several cardiac activation sequences were generated using bipolar stimulation from intramural plunge needles at different sites of the heart: left ventricle (LV), right ventricle (RV), apex, septum, and sinus. The cardiac potentials were recorded at the epicardial surface with an epicardial sock with 247 electrodes (inter-electrode spacing 6.5±1.3 mm). The torso tank had 192 silver/silver-chloride electrodes (with inter-electrode spacing 40.2±16.8 mm) distributed across the outer surface. Geometric surfaces were constructed based on electrode locations acquired during each experiment.

Geometric Variation The geometric variation used in this study are meant to model the change in cardiac position as a result of posture and the change in torso shape during the respiratory cycle. Cardiac position was parameterized similar to the variation described in Swenson *etal.* [6], representing three directions of cardiac swing, and vertical translation. Torso shape was modeled as a anterior-posterior scaling. The five total parameters were assumed to be independent and uniform in distribution.

Uncertainty Quantification We applied UQ to both the trained GNN-ECGI and Tikhonov ECGI models using PCE [10] in UncertianSCI [11]. The cardiac position and torso size were sampled using weighted Fekete points [12, 13] generating 262 sets of caridac-torso geometries. The geometries were used in both ECGI pipelines and the predicted cardiac sources were used with PCE to estimate the statistics of the model variation. We predict the model mean, median, stdev, and 8 quantile bands for each cardiac source on the pericardial surface and timestep.

3. Results

The uncertain heart position and torso size resulted in high levels of variability in cardiac potentials predicted by the trained GNN and Tikhonov resgularization. Derived metrics, such as the local activation times, showed similarly high uncertainty.

Table 3 is the summary of both Tikhonov and GNN models. We computed uncertainty of the pericardial potentials and local activation times (LATs) using polynomial chaos expansion (PCE) implemented in UncertainSCI. In general, the GNN is less sensitive to geometrical changes on pericardial potential prediction. Tikhonov method is less sensitive on predicting activation maps.

Fig. 2 shows some examples of LATs presented by mean and standard deviation over the heart surface. The graph-based model shows more variability from the geometry uncertainty on LV stimulation, while Tikhonov model has more variability on sinus and RV stimulations.

Fig. 3 are RMS potentials over heart surface. The quantile ranges show the variability because each bands represents the distribution where the darker band shows the higher probability of prediction for the signal that will be

Table 1. Uncertainty statistics of GNN and Tikhonov models on different stimulation sites.

Model	Sinus	LV	RV	Apex	Septal
GNN Potentials (mV)	2.6 ± 2.9	$\mathbf{5.2 \pm 5.0}$	$\mathbf{5.6 \pm 5.3}$	$\mathbf{3.5 \pm 2.7}$	$\mathbf{4.3 \pm 3.8}$
Tikhonov Potentials (mV)	$\mathbf{0.7 \pm 0.7}$	5.2 ± 6.0	13.9 ± 20.1	21.0 ± 24.6	30.9 ± 35.1
GNN LATs (ms)	19.7 ± 5.9	54.2 ± 17.7	63.6 ± 23.8	$\mathbf{32.9 \pm 9.3}$	$\mathbf{41.6 \pm 10.0}$
Tikhonov LATs (ms)	$\mathbf{14.9 \pm 6.6}$	$\mathbf{31.9 \pm 11.7}$	$\mathbf{46.2 \pm 14.1}$	41.3 ± 12.1	44.9 ± 14.0

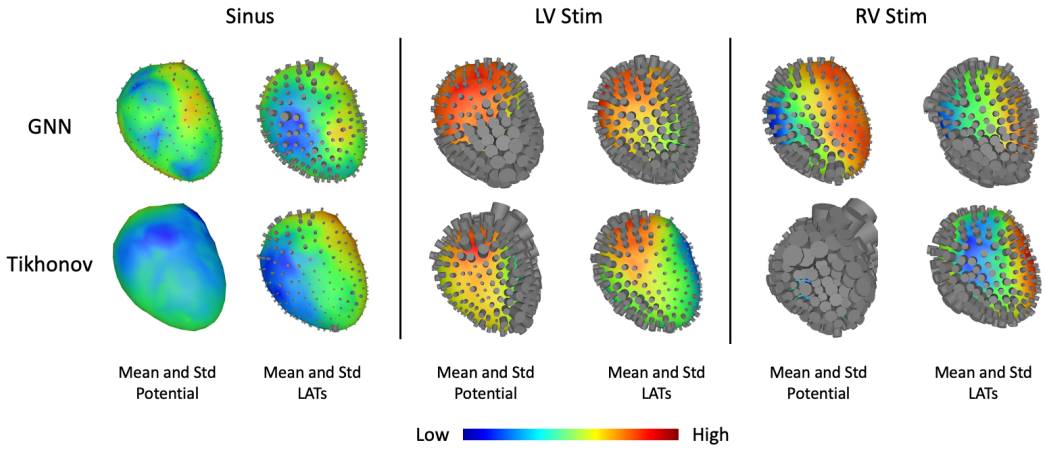

Figure 2. Spatial distribution of uncertainty of the LATs on both GNN and Tikhonov models. Colormap shows the mean and the cylinders show the standard deviation.

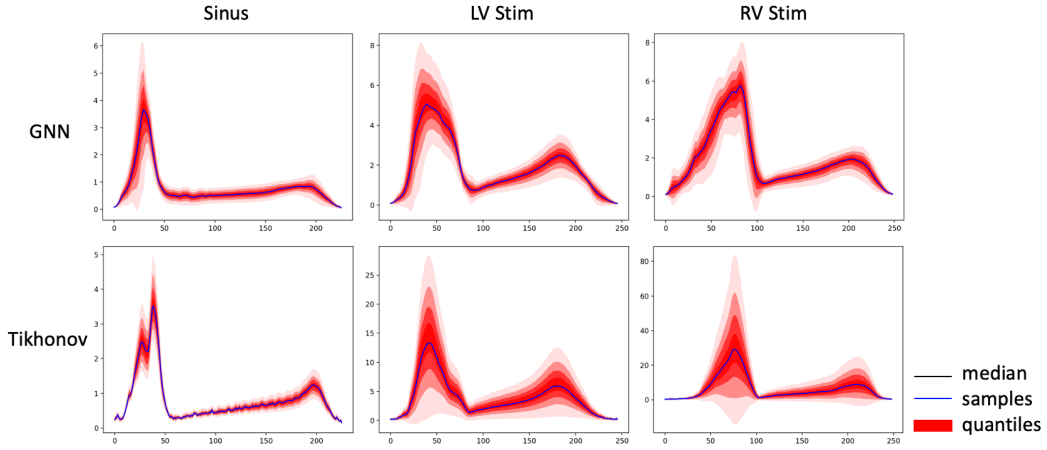

Figure 3. Uncertainty of reconstructed cardiac RMS potentials on both GNN and Tikhonov models.

more likely to fall into that region. The graph-based model has lower sensitivity of geometrical changes along the time of signal propagation and is less dependent on RMS amplitude.

Fig. 4 shows examples of the uncertainty of the simulated pericardial potential recordings . The quantile bands shows the probability of samples falling into that region. The results show consistent variation with respect to activation pattern to what we saw in other measures, with Tikhonov showing lower variability in sinus activation, but lower variability in LV and RV stimulation. The samples show in the figure (blue lines) also demonstrate extreme variability with RV stimuation predictions.

4. Conclusions

The results described in this study show a similar level of uncertainty in both the GNN and Tikhonov regularization predictions of cardiac sources resulting from cardiac and torso geometry variability. While the relative variation of the two models depended on beat and activation profile, the GNN-ECGI was less sensitive to the modeled geomet-

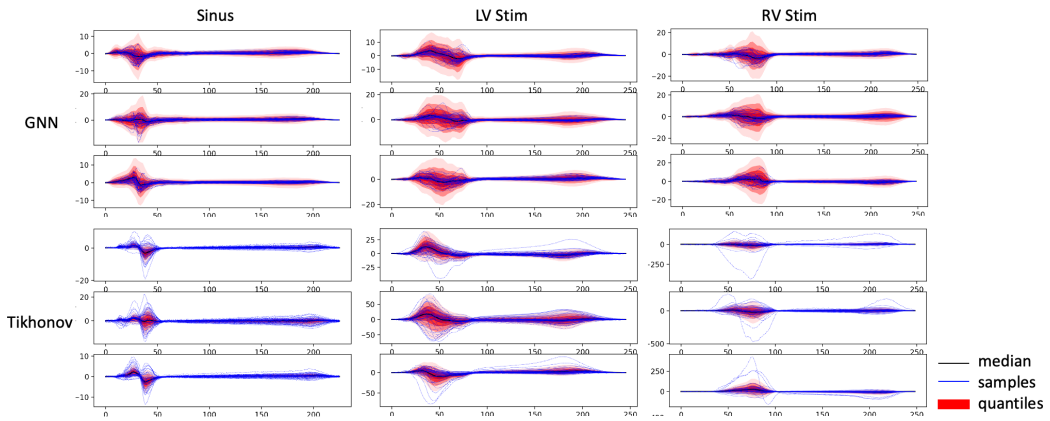

Figure 4. Examples of simulated pericardial recordings for both GNN and Tikhonov models.

ric uncertainty overall. Predicted uncertainty also demonstrates possible improvements in the GNN-ECGI model, such as including geometric variation in the training data. Better understanding of ECGI sensitivity to model geometry will also improve understanding in clinical settings and inform diagnostic and treatment predictions.

Acknowledgments

This project was supported by the National Institute of General Medical Sciences of the National Institutes of Health under grant numbers R24GM136986, U24EB029012.

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