# Segmentation Uncertainty Quantification in Cardiac Propagation Models

Jess D Tate[1], Nejib Zemzemi[2], Shireen Elhabian[1], Beáta Ondrušová[3], Machteld Boonstra[4], Peter van Dam[4], Akil Narayan[1], Dana H Brooks[5], and Rob S MacLeod[1]

[1]University of Utah, Salt Lake City, UT, USA
[2]Inria Bordeaux Sud Ouest, France
[3]Slovak University of Technology, Bratislava, Slovakia
[4]UMC Utrecht, The Netherlands
[5]Northeastern University, Boston, MA, USA

## Abstract

*A key part of patient-specific cardiac simulations is segmentation, yet the impact of this subjective and error-prone process hasn't been quantified in most simulation pipelines. In this study we quantify the dependence of a cardiac propagation model on from segmentation variability. We used statistical shape modeling and polynomial Chaos (PC) to capture segmentation variability dependence and applied its affects to a propagation model. We evaluated the predicted local activation times (LATs) an body surface potentials (BSPs) from two modeling pipelines: an EIkonal propagation model and a surface-based fastest route model. The predicted uncertainty due to segmentation shape variability was distributed near the base of the heart and near high amplitude torso potential regions. Our results suggest that modeling pipelines may have to accommodate segmentation errors if regions of interest correspond to high segmentation error. Further, even small errors could proliferate if modeling results are used to to feed further computations, such as ECGI.*

## 1. Introduction

Patient-specific cardiac simulation continues to increase in relevance in research and the clinic for predicting arrhythmias and guiding treatments. Many of the prevailing simulation methods, such as heart propagation models [1], ECG forward simulation, and Electrocardiographic Imaging (ECGI)[2, 3], rely on segmenting medical imaging to incorporate patient geometry into the biophysical models. While the deployment of these pipelines in clinical settings is eminent, uncertainty from differing strategies of translating clinical data, such as medical imaging, into values needed for computational modeling remains largely unquantified.

Using clinical data is crucial to generating tractable patient-specific cardiac models, yet it also requires the compilation of many assumptions and estimations, leading to multiple possible sources of uncertainty. Segmenting imaging data into a geometric model is one, often overlooked, source of uncertainty. We have previously shown that, when using the same patient imaging, experts from multiple research groups generate segmentations that vary widely especially the cardiac surface [4]. This variability likely affects the ECGI solutions [5], and we have used statistical shape analysis to quantify the variability of segmentation of a patient geometry [6] and incorporate the statistical shape model an ECGI pipeline to quantify the uncertainty due to segmentation variability [7].

In this study we quantify the uncertainty of cardiac propagation models from segmentation variability using a statistical shape model and polynomial Chaos emulators (PCE) [8]. We used the collaborative framework of the Consortium for ECG Imaging (CEI) to compile a cohort of cardiac segmentations for the shape model [9] and estimated the resulting uncertainty on Eikonal propagation models [10] and fastest-route models [11]. We found that predicted activation pattern uncertainty correlated with segmentation variability, and that recorded surface potentials were similarly affected.

## 2. Methods

In order to determine the effect of segmentation variability on cardiac propagation models we employed statistical shape modeling and polynomial Chaos emulators (PCE) with two cardiac propagation models with ECG simulation (Figure 1).

Segmentation variability used in the uncertainty quantification (UQ) was characterized using using statistical shape analysis. Researchers within the Consortium for ECG Imaging (CEI, ecg-imaging.org), supplied eleven ventricular segmentations from a single patient CT scan

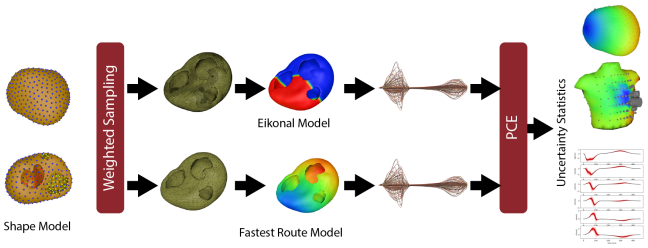


Figure 1. Pipeline to quantify the effect of shape variability on cardiac forward models.

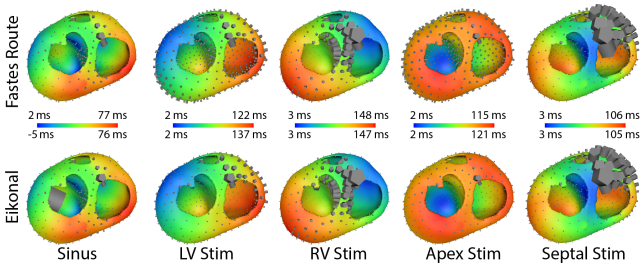


Figure 2. Predicted mean and standard deviation of the LATs. Max standard deviation is 84 ms (septal stimulation) for the fastest route model and 114 ms (sinus) for the Eikonal model.

and ShapeWorks [12] (https://www.sci.utah.edu/software/shape was used to quantify the geometric variation and formulate a parameterized shape model [9] that could be used as an input into UQ modeling pipeline. The resulting shape model captured 90% of the total variation using five modes of variation, which can be used as a parameter space to generate arbitrary cardiac geometries with the shape space.

We computed the uncertainty of propagation models resulting from shape variation using PCE in UncertainSCI (https://www.sci.utah.edu/cibc-software/uncertainsci.html). The UQ analysis treated the five shape modes as random input parameters. UncertainSCI parsimoniously sampled the parameter space using weighted approximate Fekete points [8] and the collated model outputs were used in the PCE (polynomial order of five) to derive statistics of the model output distribution [8, 13].

We quantified the uncertainty due to shape variation within two propagation models: Eikonal propagation [10], and fastest-route [11]. Each of the 262 geometries sampled from the shape model were meshed as both a high resolution tetrahedral mesh for Eikonal propagation or a low resolution triangle surface mesh for fastest route. Cardiac propagation was simulated with five activation profiles: sinus, left ventricle (LV) stimulation, right ventricle (RV) stimulation, apical stimulation, and septal stimulation. In both models, conductivity was assumed to be isotropic with 1.15 m/s conduction velocity. BSPs were computed from the transmembrane potentials generated from the Eikonal propagation model with psuedoECGs [10]. With the fastest route model, equivalent dipole layer (EDL) and boundary element method (BEM) was used to compute BSP [11]. Uncertainty in the predicted local activation times (LATs) and body surface potentials (BSPs) were both predicted with UncertainSCI.

The medical images used in this study were collected by Sapp et al. [14] and are available for open use on the EDGAR database (http://edgar.sci.utah.edu) [15] a shared resource of the CEI.

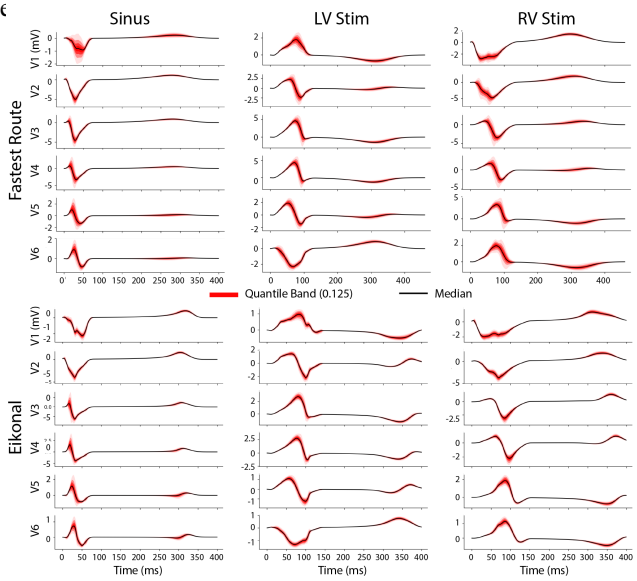


Figure 3. Predicted median and quantile regions of the precordial ECGs.

## 3. Results

The two propagation models demonstrated similar uncertainty of predicted LATs resulting from shape variability. As shown in Figure 2, the regions with the highest variability were the base of the heart and the right ventricular outflow tract (RVOT). Furthermore, model uncertainty was noticeably higher in septal and RV stimulation than in other simulated activation patterns.

The two propagation models also demonstrated similar patterns of uncertainty of predicted BSPs resulting from shape variability, yet the fastest route model showed marginally more uncertainty than the Eikonal (Figures 3, 4, & 5). Figures 3 & 4 show that model uncertainty varies over time and correlates with signal amplitude. Similarly, Figure 5 shows that model uncertainty varies over the body surface, and correlates to high signal

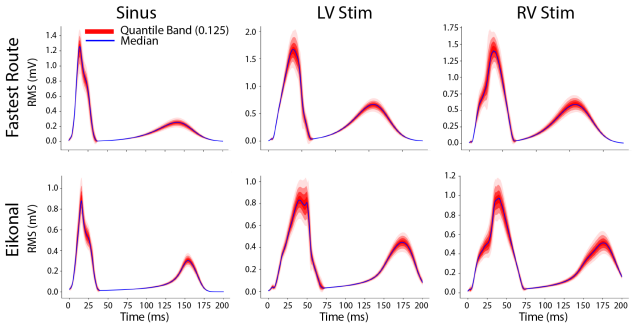


Figure 4. Predicted median and quantile regions of the BSP RMS curves.

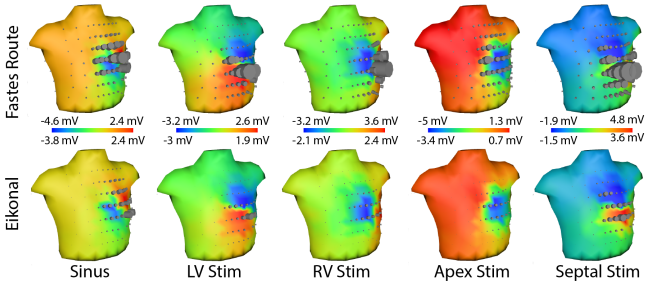


Figure 5. Predicted mean and standard deviation of the LATs. Max standard deviation is 3.7 mV (septal stimulation) for the fastest route model and 1.4 mV (sinus) for the Eikonal model.

amplitude areas and areas of high spacial gradient. Distinctions between activation profiles, in terms of uncertainty from shape variability, were not as clear as those in the predicted LATs.

## 4. Discussion and Conclusions

The goal of this paper was to quantify the uncertainty from segmentation variability in cardiac propagation models. Our results showed that both models are relatively robust to shape variability in many areas of the heart. However, some circumstances can lead to significant uncertainty in predicted LATs and BSPs. Also, despite very similar predictions in LATs uncertainty between the two propagation models, the fastest route model showed noticeably higher uncertainty in predicted BSP, indicating that greater sensitivity to shape error with some modeling methods.

Both propagation models predicted greater uncertainty from segmentation error in predicted LATs near the RVOT and the base of the heart. These areas of high uncertainty correlate to areas of high shape variability [9] and areas of high uncertainty in predicted pericardial potentials from ECGI [7]. However, not all activation profiles were affected the same, with RV and septal stimulation showing higher uncertainty in these same regions, while the uncertainty in the rest of the heart relatively consistent across activation profiles. The shape model captured segmentations of divergent strategies, leading to geometries with differing numbers of segmented ostia and accessory pathways in base and RVOT [9]. Highly variable LATs may be expected within this context, yet this level of variability from a cohort of expert segmentations highlight the need to formulate clear and accurate strategies for segmenting the base and RVOT regions of the heart to minimize the variability of accessory pathways.

The differing levels of predicted BSP uncertainty between the two modeling pipelines from the same segmentation variability demonstrate possible avenues for downstream modeling errors from segmentation variability. The uncertainty in predicted LATs is not notably more in fastest route than Eikonal, yet the predicted BSPs shows a marked difference in uncertainty. While some of the data and geometry processing necessarily diverge in the two pipelines, it is also possible that the forward ECG methods used with the fastest route method (EDL and BEM) may be more sensitive to segmentation variability than those used by the Eikonal propagation model (psuedoECGs). More in-depth analysis of the contrasting forward modeling methods is needed to clarify this discrepancy.

In this paper we demonstrated a modeling pipeline with open source tools to evaluate the uncertainty from segmentation variability in cardiac propagation models that could be adapted to many other types of geometry based models. We showed that segmentation variability can cause high levels of uncertainty in cardiac propagation models by generating variable accessory pathways. We also observed propagation of model uncertainty to the predict BSP that varied based on methodology that might extend to other pipelines that rely on these propagation models and forward methods, such as ECGI. Implementing similar UQ techniques on downstream modeling pipelines will help identify and minimize propagated errors.

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Address for correspondence:

Jess Tate
Scientific Computing and Imaging Institute
WEB, 72 South Campus Drive, Rm 3750
Salt Lake City, UT 84112
jess@sci.utah.edu