- 1 Reconstruction of three-dimensional biventricular activation based on the 12-lead ECG
- 2 via patient-specific modeling
- 3 **Authors:** Simone Pezzuto, PhD¹; Frits W Prinzen, PhD²; Mark Potse, PhD^{3,4,5};
- 4 Francesco Maffessanti, PhD¹; François Regoli, MD^{1,6}; Maria Luce Caputo, MD^{1,6};
- 5 Giulio Conte, MD, PhD^{1,6}, Rolf Krause, PhD¹; Angelo Auricchio, MD, PhD^{1,6}.
- ⁶ ¹Center for Computational Medicine in Cardiology, Institute of Computational Science,
- 7 Università della Svizzera italiana, Lugano, Switzerland
- ⁸ ²Dept. of Physiology, CARIM, Maastricht University, Maastricht, The Netherlands
- ⁹ ³Univ. Bordeaux, IMB, UMR 5251, Talence, France
- ¹⁰ ⁴CARMEN Research Team, Inria Bordeaux Sud-Ouest, Talence, France
- ⁵IHU Liryc, fondation Bordeaux Université, Pessac, France
- ¹² ⁶Division of Cardiology, Fondazione Cardiocentro Ticino, Lugano, Switzerland
- 13 Word count (excluding tables and references): 3491 (max. 3500)
- 14 **References:** 19 (max. 20)
- 15 Short title: Activation reconstruction from 12-lead ECG
- 16 Address of correspondence:
- 17 Simone Pezzuto, PhD
- 18 Center for Computational Modeling in Cardiology,
- 19 Institute of Computational Science, Università della Svizzera italiana,
- 20 Via Giuseppe Buffi 13, CH-6904 Lugano, Switzerland
- 21 E-mail: <u>simone.pezzuto@usi.ch</u>
- 22 Phone (office): +41 58 666 4976
- 23

24 Structured Abstract

Aims. Non-invasive imaging of electrical activation requires high-density body surface potential mapping. The 9 electrodes of the 12-lead ECG are insufficient for a reliable reconstruction with standard inverse methods. Patient-specific modeling may offer an alternative route to physiologically constraint the reconstruction. The aim of the study was to assess the feasibility of reconstructing the fully 3D electrical activation map of the ventricles from the 12-lead ECG and magnetic resonance (CMR).

31 **Methods.** Ventricular activation was estimated by iteratively optimizing the parameters

32 (conduction velocity and sites of earliest activation) of a patient-specific model to fit the

simulated to the recorded ECG. Chest and cardiac anatomy of 11 patients (QRS duration 126-

180 ms, documented scar in two) were segmented from CMR images. Scar presence was

assessed by MR contrast enhancement. Activation sequences were modelled with an eikonal

equation and ECGs with lead field theory. Validation was performed by comparing

37 reconstructed activation maps with invasive electroanatomical mapping of the coronary

38 sinus/veins (CS) and the right (RV) and left ventricular (LV) endocardium.

39 **Results.** The QRS complex was correctly reproduced by the model (Pearson's correlation

40 r=0.923). Reconstructions accurately located the earliest and latest activated LV regions

41 (median barycenter distance 8.2 mm, IQR 8.8 mm). Correlation of simulated to recorded

42 activation was very good at LV endocardium (r=0.83), and good at CS (r=0.68) and RV

43 endocardium (r=0.58).

44 **Conclusion.** Non-invasive assessment of biventricular 3D activation using the 12-lead ECG

and MR imaging is feasible. Potential applications include patient-specific modeling and pre /per-procedural evaluation of ventricular activation.

47

48 Keywords. 12-lead ECG; 3D activation; eikonal model; patient-specific modelling

50 Condensed abstract

- 51 A model-based reconstruction of the three-dimensional activation map relying only on the 12-
- 52 lead ECG and patient-specific anatomy was investigated. The reconstruction was achieved by
- 53 fitting the parameters of a patient-specific model (conduction velocity, sites of earliest
- activation) to the recorded ECG. In 11 patients, the method correctly reproduced the surface
- 55 QRS complex. The reconstructed activation map correlated strongly with the invasive
- 56 electroanatomical mapping.

58 What's new?

59	•	Reconstruction of 3D activation map with only 12-lead ECG, patient-specific anatomy
60		and CMR-derived scar using an eikonal model for the electric activation
61	•	Validation of reconstruction against RV and LV endocardial, and LV epicardial
62		invasive, high-density electroanatomic maps in 11 patients
63	•	Physiologically accurate conduction with heterogeneities (scar, fast endocardial layer)
64		and anisotropy (fibers)
65	•	Enabling technology for non-invasive individualization of patient-specific models
66		
67		

68 Introduction

The standard 12-lead electrocardiogram (ECG) is the most routinely used, inexpensive and non-invasive modality to record the electrical activity of the heart, but its diagnostic capability has acknowledged limits. In particular, the surface ECG does not provide quantitative information about the activation sequence in the heart.

Non-invasive electrocardiographic imaging, also called ECG mapping, overcomes at 73 least some of the limitations of the standard ECG. ECG mapping combines information from 74 many (usually 150-250) electrodes with knowledge of the geometry of the heart and torso of 75 the patient to depict the electric activity of the heart.¹ It is a general-purpose tool that can 76 reconstruct potentials, electrograms, and activation and repolarization patterns on either the 77 epicardium or, less commonly, the endocardium. Some technologies based on ECG mapping 78 have been extensively validated in experimental, animal and clinical studies, with convincing 79 results.²⁻⁵ However, ECG mapping relies on a large number of electrodes, placed on the 80 patient's torso at the time of geometry acquisition using cardiac imaging as well as during the 81 clinical intervention, thus requiring dedicated technical support and additional costs. 82 Therefore, despite the advantages, its adoption in the clinical workflow is still limited. 83

In the present study we assess the possibility to reconstruct the activation map relying 84 only on the 12-lead ECG for the electric data, by taking advantage of physiological and 85 anatomical knowledge implemented in a patient-specific model. The parameters of the model, 86 regional conduction velocities and sites of earliest activation, are automatically optimized to 87 fit the simulated to the recorded ECG. The fitted patient-specific model can calculate almost 88 real-time the activation sequence and may therefore enable model-assisted therapeutic 89 intervention. Proof-of-principle validation was performed on a small, yet heterogeneous 90 cohort of patients possibly with a scar by an extensive comparison of the calculated activation 91 map against the invasively acquired high-density electro-anatomic endocardial map. 92

94 Methods

95 Study population

96 Eleven heart failure patients were retrospectively included in the study. A 12-lead ECG, a

97 clinically indicated magnetic resonance (MR) scan with late gadolinium-enhancement (LGE),

and an electrophysiological study including an electroanatomic mapping (EAM) procedure

99 were performed in all the patients before device implantation (see supplemental material).

100 The institutional review board approved the study protocol, and all patients gave written and

101 oral informed consent for the investigation. The study was performed in compliance with the

102 Declaration of Helsinki.

103 **Construction of the patient-specific model**

Figure 1 shows the overall workflow from data acquisition to model construction and validation. The eikonal model for simulating myocardial activation and body surface ECG has been previously described.⁶ In summary, the electrical activation originated from a limited number (1 to 10) of early activation sites (EASs) and spread across the active myocardium with given spatially varying, direction-dependent conduction velocity. The propagation was faster in the fiber direction than in the cross-fiber direction. Scar was modeled as nonconductive tissue. The ORS complex of the 12-lead ECG was simulated by using the formula:

$$V_k(t) = \int_{\Omega} \boldsymbol{G}_{\rm in}(x) \nabla U(t - \tau(x)) \cdot \nabla Z_k(x) \, \mathrm{d}x,$$

which combines the lead fields in the torso $Z_k(x)$, one per lead k = 1, ..., 12, and a template action potential U(t) shifted in time according to activation onset $\tau(x)$. The integration domain Ω was the 3D active myocardial tissue, with intracellular conductivity tensor $G_{in}(x)$. For the computation of the lead fields, the torso included lungs, blood masses, active and nonconductive myocardium (with anisotropy), skeletal muscles, and skin. Further details on the construction of the anatomical model and the computation of the lead fields are available in the supplemental material.

118 In order to reproduce the recorded QRS complex, the number of EASs, along with their

locations and onsets, and the conduction velocity in 4 distinct regions (LV, RV and LV, RV

120 fast endocardial layer) were automatically adapted to minimize the least-squares error

between the simulated and recorded QRS complexes. Several other parameters (electric

conductivities, membrane model) were left unchanged from those reported in previous 122 studies. The initial guess for the optimized parameters was the same in all the patients. 123 The minimization procedure consisted of 2 phases. The first phase optimized the global CV 124 125 and number of EASs, along with an initial estimate of their location and activation onset. Simulations started with at least 100 tentative EASs uniformly distributed across the LV and 126 RV endocardium (excluding scar), all simultaneously activating with zero onset and with 127 fixed location along the whole procedure. The optimization of the parameters proceeded 128 iteratively as follows: firstly, onsets of all EASs were optimized to locate the region of 129 earliest activation; secondly, a shift-and-scale transformation of the activation map, obtained 130 by adjusting CV and onset, aimed for an optimal alignment of simulated and recorded ECG; 131 thirdly, EASs with negligible impact on the activation map (in terms of region of influence) 132 were progressively removed. The three steps were iterated until no further reduction in the 133 error was possible. In the second optimization phase the number of EASs was fixed whereas 134

their location and onset were optimized in combination with the local CV, until convergence.

136 Validation

135

EAMs and patient-specific anatomy were aligned by means of a translation and the acquired 137 points were projected onto the corresponding anatomical region (LV or RV endocardium, LV 138 139 epicardium). Validation was performed by comparing the recorded and reconstructed activation time both pointwise and regionally. The LV earliest and latest activated regions 140 141 (EAR and LAR) were presented using a bull's-eye plot. The EAR and LAR were respectively defined as the earliest 10% and the latest 10% of activated endocardium. The endocardial 142 breakthrough point (BP) and latest activated point (LAP) were defined as the projected 143 barycenter of the EAR and LAR, respectively. A trans-septal time (TST) was defined as the 144 145 earliest LV breakthrough time, whereas the total activation time (TAT) was the latest activation time within the LV endocardium. The overlap (OVL) between recorded and 146 reconstructed activation was evaluated as area of the overlap when 20% of the total 147 endocardium was activated, divided by 0.2. 148

149 Statistical analysis

150 Recorded and simulated ECG were compared in terms of Pearson's correlation, relative root-

- 151 mean-square error (RMSE) and QRS duration. A similar analysis was applied to the
- 152 pointwise comparison to EAMs. All distances were computed using the Euclidean distance.

- All quantities are reported in mean \pm SD, or median and 1st and 3rd quartile, if not indicated
- 154 differently.

156 **Results**

157 A summary of the demographic characteristics of the included patients is shown in Table 1.

158 On average 265±109 endocardial activation points per patient were acquired. In 11 patients,

159 186±59 LV endocardial points were collected, in 6 patients an additional 71±22 points in the

- 160 RV, and in 7 patients 63±19 points were recorded on the LV epicardium by introducing the
- 161 mapping catheter into the coronary sinus and whenever possible in the coronary veins.

162 **Detection of EASs**

An illustrative example of the fitted patient-specific models is reproduced in Figure 2 163 for an IVCD patient with coronary artery disease (patient #4). The patient has a non-LBBB 164 QRS morphology and an extensive sub-endocardial scar located in the LV antero-lateral wall. 165 The algorithm identified 14 EASs, 7 RV and 7 LV. No RV-LV delay was observed. In the 166 LV, BPs were in the septal area both inferiorly and anteriorly, with a slightly higher 167 occurrence in the inferior sectors. The simulated and recorded QRS complexes correlated 168 excellently (r= 0.978). The BP and LAP localization errors were 11.1 mm and resp. 8.9 mmm 169 respectively. Notably, 4 EARs were correctly identified, with 2 EARs in the antero-septal area 170 and 2 EARs in the inferior-septal area, very close to the recorded EAR in the same area. 171 Pointwise correlation between calculated and measured points was 0.78 and OVL 0.4. 172

173 **Overall accuracy of reconstructed activation**

A pointwise comparison of reconstructed activation at points from EAM (Table 2) showed 174 very high Pearson's correlation (r=0.815), particularly at LV endocardium (r=0.833). In the 175 RV endocardium and coronary sinus/veins the correlation was lower (r=0.576 and r=0.677). 176 The Bland-Altman analysis showed no bias (0.45 ms) and limits of agreement (LoA) of -42.7177 ms and +43.6 ms (2856 points). On the LV epicardium and endocardium, the reconstruction 178 was good (r>0.7) in 10 patients (91%) and modest only in patient #3 (r=0.33). On the RV 179 endocardium Pearson correlation per patient was generally modest (r>0.5 in 4 patients out of 180 6) and poor in patient #6 (r=0.18). A relatively large bias of 27 ms was observed on the RV 181 endocardium with LoA -18 ms and 72 ms. 182

The estimated TST obtained from the fitted model closely matched the measured TST (difference between reconstructed and recorded was -15.5 ± 16.5 ms) in all but one. The reconstructed TAT slightly overestimated the recorded one, with a difference of 25.7 ± 22 ms.

The BP and LAP in the LV were accurately identified in the correct AHA sector on the bull's-eye plot in the majority of the patients (72%). In the remaining cases, BP was placed in the neighbor segments (Figure 3). The distance between the calculated and the recorded BP was 13.5 [6.9,16.1] mm, and the OVL was 0.75 [0.56,0.79]. The LAP was also accurately captured by the reconstructed activation map, 8.1 [6.1,14.5] mm off the recorded

191 position.

192 Accuracy of fitting the ECG

- 193 Overall, the fitted QRS complex was highly correlated to the recorded QRS complex (r=0.92)
- and correlation was >0.9 in 9 out of 11 patients (82%). Per-patient correlation (Table 3)
- ranged from 0.84 (patient #7) to 0.98 (patient #6). The QRS duration was well captured,
- reporting an error (reconstructed minus recorded) of -3.0 [-17.37,5.28] ms. Overall, V1-V4
- 197 showed very high correlation while lead V6 and aVR showed modest correlation.

199 Discussion

This study shows that a mathematical model can accurately reconstruct the volumetric propagation sequence of the ventricles in heart-failure patients. In contrast to commercially available ECG mapping technologies, it does not require hundreds of electrodes; we obtained our results with only the 12-lead ECG and standard imaging data. The method can be easily integrated in existing EAM systems, possibly reducing mapping time, and increasing localization accuracy.

Our method is neither the first to require only a 12-lead ECG,^{7,8} nor the first to predict the 206 activation sequence in the entire ventricular volume,⁹ but it is the first to achieve both of these 207 feats without compromising the physiological accuracy or strongly limiting the applicability 208 of the approach. Our method combines the best of two worlds: ECG mapping^{1,2,7,9} and 209 patient-specific modeling.^{10–12} Due to a highly optimized implementation the reconstruction is 210 211 competitive in terms of time to solution to other ECG mapping approaches. At the same time, the accuracy of its ECG prediction is comparable to the gold standard, the bidomain model.⁶ 212 We achieve this accuracy by using a volumetric conduction model, necessary to incorporate 213 the effect of tissue anisotropy on the potential field generated by the activation wavefront. 214 This automatically results in a fully 3D prediction of the activation sequence. The activation 215 sequence itself was simulated realistically with an anisotropic eikonal equation. Importantly, 216 we did not observe potentially unphysiological lines of block and U-shaped activation, often 217 present in ECG mapping, because conduction velocity cannot change abruptly unless directly 218 specified in the model. Particularly relevant is the presence in our model of a thin, fast 219 endocardial layer in the LV and RV, which better captures the physiological behavior in this 220 region.¹³ 221

222 Accuracy

We quantified the accuracy of the reconstruction as the correlation of invasively measured and calculated activation times, their timing difference and the precision of locating the early and late activated regions. Commercially-available ECG mapping systems, while extensively tested in experimental and animal studies, have been validated in a clinical setting with these metrics only very recently and still with a limited coverage of RV and LV endocardium.^{3,5,15,16} The patient population in the present study included patients with coronary artery disease and a wide range of QRS duration and morphology, which in the vast
 majority of studies of standard ECG mapping systems was missing.

The overall correlation of the activation map in the present study (r=0.82) is 231 comparable to those reported for ECG mapping in controlled isolated hearts ($r=0.68\pm0.265$), 232 in-vivo animal experiments (r=0.82), and in clinical studies during pacing (r=0.66).^{3,4,15} 233 Studies performed during sinus rhythm, better reflecting our cohort, showed significantly 234 lower correlation (r close to zero).¹⁵ Similarly, our localization error of BP and LAP in the LV 235 (12.2±8.8 mm) compared well with those of the animal studies (9.1±0.6 and 10 mm, 236 respectively) and is much better than those reported in the clinical study in sinus rhythm.¹⁵ In 237 the analysis we also considered the similarity (in terms of overlap) between recorded and 238 reconstructed earliest activation (0.69 ± 0.17) as a metric for accuracy in the reconstruction. 239 While a small localization error suggests an accurate reconstruction of BP and LAP location, 240 a large overlap indicates that conduction properties are also correct. 241

The reconstruction of the CS/veins map adequately reproduced the invasive 242 recordings. In contrast, the RV activation reconstruction was modest in terms of correlation 243 (r=0.58) and showed on average a deviation from the EAM of 27 ms. A closer inspection of 244 the Bland-Altman plot suggests that points in the earliest activated region were well 245 reproduced while late-activated points were considerably delayed in the reconstructed map. 246 The RV contributes less than the LV to the ECG, and the least-squares minimization used 247 here tends to ignore small deviations in amplitude, hence limiting the accuracy. Additionally, 248 the alignment of the recorded RV points to the anatomy is problematic and may be affected 249 by large uncertainty, because of the concave shape of the chamber. 250

251 Patient-specific modelling

By virtue of its model-based nature, our approach has the potential to further improve the individualization in patient-specific modelling, an emerging paradigm aiming at supporting personalized therapeutic interventions.¹⁷ Non-invasive mapping of ectopic foci and personalization of cardiac models from 12-lead ECG has already been investigated by others.^{7,8,10–13} These methods are accurate but often rely on the somewhat restrictive assumption that only a single EAS is to be identified. We overcome this assumption with a novel strategy to identify an optimal number and location of sites of earliest activation.

259 Robustness of validation

The activation map extrapolated from the invasive mapping system may be affected by 260 several uncertainties. The detection of the activation time from EGM could be difficult 261 because of fractionation and far field signal in the unipolar readings, and direction-262 dependency in bipolar signals.¹⁸ In addition, the spatial location of imaged points needs to be 263 registered to the electrode positions. The combination of both these uncertainties (in space 264 and in time) may affect the comparison, especially for BP and LAP localization. In this work 265 we opted for the more robust definition of BP (resp. LAP) as the barycenter of the EAR (resp. 266 LAR). In a Monte Carlo study, we found that the localization error of BP has significantly 267 lower variance if defined as above instead as the earliest activated point. (See supplemental 268 269 material.)

270 Perspectives on clinical application

Our method could be included in the screening workflow of patients who are candidate to CRT as well as in selecting pacing targets. The measurement of the time interval between RV and LV, or the time between Q wave on surface ECG and LV at the time of CRT implantation has been predictive of both acute and chronic response to CRT.¹⁹ The method could easily estimate both RV-LV timing and Q-LV time and thus provide a novel way for patient selection and pre-procedural planning of RV and LV lead placement. Patient-specific activation patterns can be calculated right at the time of pacing lead placement.

278 Study limitations

The patient-specific model has several parameters with considerable uncertainty. This 279 is an undeniable problem of current cardiac models and, more generally, biological systems. 280 The objective function is highly non-linear and non-convex with respect to the parameters of 281 the model, hence given the limited amount of data we use for the fitting, it is plausible that 282 multiple combinations of parameters yield similar activation maps and surface ECG. The 283 solution may therefore depend on the initial guess for the parameters and the optimization 284 algorithm. In order to alleviate this problem, we designed the first phase of the algorithm to 285 provide a possible initial guess. More advanced global optimization techniques may offer a 286 more robust approach, albeit with a higher computational footprint. 287

The eikonal model does not cover the full spectrum of activation patterns. This may limit its applicability. Most notably, reentrant activation is not admissible in our current formulation.

The study was admittedly based on a small patient cohort. However, this cohort was heterogeneous, with QRS duration ranging from 126 to 180 ms, different ventricular conduction abnormalities and variable underlying disease (e.g. scar). Importantly, the validation measurements consisted of high-resolution endocardial mapping in both ventricles and epicardial LV measurements in heart failure patients. In contrast, the majority of the previous ECG imaging studies have only considered epicardial data during SR, endocardial data with pacing from a single site, or data derived from in silico models.

The validation analysis in this study was not performed blindly to the intracardial mapping. To avoid a possible bias, we employed the same initial guess in the algorithm for all the patients, despite the heterogeneity of the cohort.

Currently, the model requires an accurate segmentation and mesh-construction from imaging data, which may require several hours per patient. For the majority of applications, a preparatory phase of several hours is reasonable and it does not disrupt the clinical workflow. Nonetheless, time to segmentation can nowadays be improved significantly by a combination of statistical atlases and machine learning.

Finally, scar was assessed by LGE-MRI acquisitions, which might not be routinely available. We also did not consider the border zone of the scar in the model, although the model can easily allow for it.

310 Conclusions

- 311 A 12-lead ECG-based technique for reconstructing cardiac activation was developed and
- validated. The methodology achieved very good endocardial accuracy, opening the possibility
- 313 for a non-invasive pre- and peri-procedural evaluation of activation map during intrinsic sinus
- rhythm and, potentially, for guiding optimal lead placement.
- 315
- **Funding:** Theo Rossi di Montelera Foundation (Lausanne, Switzerland); Metis Foundation
- 317 Sergio Mantegazza (Lugano, Switzerland); Fidinam Foundation (Lugano, Swizerland); Swiss
- Heart Foundation (Bern, Switzerland); SNSF project 32003B_165802 (Bern, Switzerland);
- 319Horten Foundation (Castelrotto, Switzerland); CSCS—Swiss National Supercomputing
- 320 Centre production grant s778 (Lugano, Switzerland).
- 321 **Disclosures:** AA is consultant with Boston Scientific, Backbeat, Biosense Webster, Cairdac,
- 322 Corvia, Daiichi-Sankyo, Medtronic, Merit, Microport CRM, Philips, and V-Wave; received
- 323 speakers' fee from Daiichi-Sankyo, Boston Scientific, Biosense Webster, Medtronic,
- 324 Microport CRM, and Philips; participates in clinical trials sponsored by Boston Scientific,
- 325 Medtronic, Microport CRM, and Zoll Medical; and has intellectual properties assigned to
- Boston Scientific, Biosense Webster, and Microport CRM. FP has received research grants
- from Medtronic, Abbott, Microport CRM, Biotronik and Biosense Webster and speakers fee
- from Medtronic, Abbott and Microport CRM; and he reports intellectual property with Boston
- 329 Scientific, Medtronic and Biosense Webster. FM reports intellectual property with Biosense
- 330 Webster. FR is consultant for Daiichi-Sankyo, Medtronic, and Bayer. All the other authors
- have nothing to disclose.
- 332 Data availability: The data underlying this article cannot be shared publicly for the privacy
 333 of individuals that participated in the study. The data will be shared on reasonable request to
 334 the corresponding author.

References

337 338	1.	Ramanathan C, Ghanem RN, Jia P, Ryu K, Rudy Y. Noninvasive electrocardiographic imaging for cardiac electrophysiology and arrhythmia. <i>Nat Med</i> 2004; 10 :422–8.
339	2.	Berger T, Fischer G, Pfeifer B, Modre R, Hanser F, Trieb T, et al. Single-Beat
340		Noninvasive Imaging of Cardiac Electrophysiology of Ventricular Pre-Excitation. J
341		<i>Am Coll Cardiol</i> 2006; 48 :2045–52.
342	3.	Cluitmans MJM, Bonizzi P, Karel JMH, Das M, Kietselaer BLJH, Jong MMJ de, et al.
343		In Vivo Validation of Electrocardiographic Imaging. JACC Clin Electrophysiol
344		2017; 3 :232–42.
345	4.	Bear LR, LeGrice IJ, Sands GB, Lever NA, Loiselle DS, Paterson DJ, et al. How
346		Accurate Is Inverse Electrocardiographic Mapping? Circ Arrhythmia Electrophysiol
347		2018;11:1–12.
348	5.	Graham AJ, Orini M, Zacur E, Dhillon G, Daw H, Srinivasan NT, et al. Simultaneous
349		Comparison of Electrocardiographic Imaging and Epicardial Contact Mapping in
350		Structural Heart Disease. Circ Arrhythmia Electrophysiol 2019;12:e007120.
351	6.	Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a
351 352	6.	Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a Rapid Anisotropic Model for ECG Simulation. <i>Front Physiol</i> 2017; 8 :265.
351 352 353	6. 7.	 Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a Rapid Anisotropic Model for ECG Simulation. <i>Front Physiol</i> 2017;8:265. Misra S, Van Dam P, Chrispin J, Assis F, Keramati A, Kolandaivelu A, <i>et al.</i> Initial
351 352 353 354	6. 7.	 Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a Rapid Anisotropic Model for ECG Simulation. <i>Front Physiol</i> 2017;8:265. Misra S, Van Dam P, Chrispin J, Assis F, Keramati A, Kolandaivelu A, <i>et al.</i> Initial validation of a novel ECGI system for localization of premature ventricular
351 352 353 354 355	6. 7.	 Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a Rapid Anisotropic Model for ECG Simulation. <i>Front Physiol</i> 2017;8:265. Misra S, Van Dam P, Chrispin J, Assis F, Keramati A, Kolandaivelu A, <i>et al.</i> Initial validation of a novel ECGI system for localization of premature ventricular contractions and ventricular tachycardia in structurally normal and abnormal hearts. <i>J</i>
351 352 353 354 355 356	6. 7.	 Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a Rapid Anisotropic Model for ECG Simulation. <i>Front Physiol</i> 2017;8:265. Misra S, Van Dam P, Chrispin J, Assis F, Keramati A, Kolandaivelu A, <i>et al.</i> Initial validation of a novel ECGI system for localization of premature ventricular contractions and ventricular tachycardia in structurally normal and abnormal hearts. <i>J</i> <i>Electrocardiol</i> Elsevier Inc; 2018;51:801–8.
 351 352 353 354 355 356 357 	6. 7. 8.	 Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a Rapid Anisotropic Model for ECG Simulation. <i>Front Physiol</i> 2017;8:265. Misra S, Van Dam P, Chrispin J, Assis F, Keramati A, Kolandaivelu A, <i>et al.</i> Initial validation of a novel ECGI system for localization of premature ventricular contractions and ventricular tachycardia in structurally normal and abnormal hearts. <i>J Electrocardiol</i> Elsevier Inc; 2018;51:801–8. Alawad M, Wang L. Learning domain shift in simulated and clinical data: Localizing
 351 352 353 354 355 356 357 358 	6. 7. 8.	 Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a Rapid Anisotropic Model for ECG Simulation. <i>Front Physiol</i> 2017;8:265. Misra S, Van Dam P, Chrispin J, Assis F, Keramati A, Kolandaivelu A, <i>et al.</i> Initial validation of a novel ECGI system for localization of premature ventricular contractions and ventricular tachycardia in structurally normal and abnormal hearts. <i>J Electrocardiol</i> Elsevier Inc; 2018;51:801–8. Alawad M, Wang L. Learning domain shift in simulated and clinical data: Localizing the origin of ventricular activation from 12-lead electrocardiograms. <i>IEEE Trans Med</i>
 351 352 353 354 355 356 357 358 359 	6. 7. 8.	 Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a Rapid Anisotropic Model for ECG Simulation. <i>Front Physiol</i> 2017;8:265. Misra S, Van Dam P, Chrispin J, Assis F, Keramati A, Kolandaivelu A, <i>et al.</i> Initial validation of a novel ECGI system for localization of premature ventricular contractions and ventricular tachycardia in structurally normal and abnormal hearts. <i>J Electrocardiol</i> Elsevier Inc; 2018;51:801–8. Alawad M, Wang L. Learning domain shift in simulated and clinical data: Localizing the origin of ventricular activation from 12-lead electrocardiograms. <i>IEEE Trans Med Imaging</i> IEEE; 2019;38:1172–84.
 351 352 353 354 355 356 357 358 359 360 	 6. 7. 8. 9. 	 Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a Rapid Anisotropic Model for ECG Simulation. <i>Front Physiol</i> 2017;8:265. Misra S, Van Dam P, Chrispin J, Assis F, Keramati A, Kolandaivelu A, <i>et al.</i> Initial validation of a novel ECGI system for localization of premature ventricular contractions and ventricular tachycardia in structurally normal and abnormal hearts. <i>J Electrocardiol</i> Elsevier Inc; 2018;51:801–8. Alawad M, Wang L. Learning domain shift in simulated and clinical data: Localizing the origin of ventricular activation from 12-lead electrocardiograms. <i>IEEE Trans Med Imaging</i> IEEE; 2019;38:1172–84. Han C, Pogwizd SM, Killingsworth CR, He B. Noninvasive imaging of three-
 351 352 353 354 355 356 357 358 359 360 361 	6. 7. 8. 9.	 Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a Rapid Anisotropic Model for ECG Simulation. <i>Front Physiol</i> 2017;8:265. Misra S, Van Dam P, Chrispin J, Assis F, Keramati A, Kolandaivelu A, <i>et al.</i> Initial validation of a novel ECGI system for localization of premature ventricular contractions and ventricular tachycardia in structurally normal and abnormal hearts. <i>J Electrocardiol</i> Elsevier Inc; 2018;51:801–8. Alawad M, Wang L. Learning domain shift in simulated and clinical data: Localizing the origin of ventricular activation from 12-lead electrocardiograms. <i>IEEE Trans Med Imaging</i> IEEE; 2019;38:1172–84. Han C, Pogwizd SM, Killingsworth CR, He B. Noninvasive imaging of three-dimensional cardiac activation sequence during pacing and ventricular tachycardia.
 351 352 353 354 355 356 357 358 359 360 361 362 	6. 7. 8. 9.	 Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a Rapid Anisotropic Model for ECG Simulation. <i>Front Physiol</i> 2017;8:265. Misra S, Van Dam P, Chrispin J, Assis F, Keramati A, Kolandaivelu A, <i>et al.</i> Initial validation of a novel ECGI system for localization of premature ventricular contractions and ventricular tachycardia in structurally normal and abnormal hearts. <i>J Electrocardiol</i> Elsevier Inc; 2018;51:801–8. Alawad M, Wang L. Learning domain shift in simulated and clinical data: Localizing the origin of ventricular activation from 12-lead electrocardiograms. <i>IEEE Trans Med Imaging</i> IEEE; 2019;38:1172–84. Han C, Pogwizd SM, Killingsworth CR, He B. Noninvasive imaging of three-dimensional cardiac activation sequence during pacing and ventricular tachycardia. <i>Heart Rhythm</i> 2011;8:1266–72.
 351 352 353 354 355 356 357 358 359 360 361 362 363 	 6. 7. 8. 9. 10. 	 Pezzuto S, Kal'avský P, Potse M, Prinzen FW, Auricchio A, Krause R. Evaluation of a Rapid Anisotropic Model for ECG Simulation. <i>Front Physiol</i> 2017;8:265. Misra S, Van Dam P, Chrispin J, Assis F, Keramati A, Kolandaivelu A, <i>et al.</i> Initial validation of a novel ECGI system for localization of premature ventricular contractions and ventricular tachycardia in structurally normal and abnormal hearts. <i>J Electrocardiol</i> Elsevier Inc; 2018;51:801–8. Alawad M, Wang L. Learning domain shift in simulated and clinical data: Localizing the origin of ventricular activation from 12-lead electrocardiograms. <i>IEEE Trans Med Imaging</i> IEEE; 2019;38:1172–84. Han C, Pogwizd SM, Killingsworth CR, He B. Noninvasive imaging of three-dimensional cardiac activation sequence during pacing and ventricular tachycardia. <i>Heart Rhythm</i> 2011;8:1266–72. Villongco CT, Krummen DE, Stark P, Omens JH, McCulloch AD. Patient-specific

365		in bundle branch block. Prog Biophys Mol Biol Elsevier Ltd; 2014;115:305-13.
366 367	11.	Zettinig O, Mansi T, Neumann D, Georgescu B, Rapaka S, Seegerer P, et al. Data- driven estimation of cardiac electrical diffusivity from 12-lead ECG signals. <i>Med</i>
368		Image Anal Elsevier B.V.; 2014;18:1361–76.
369	12.	Giffard-Roisin S, Delingette H, Jackson T, Webb J, Fovargue L, Lee J, et al. Transfer
370		learning from simulations on a reference anatomy for ECGI in personalized cardiac
371		resynchronization therapy. IEEE Trans Biomed Eng 2019;66:343-53.
372	13.	Lee AWC, Nguyen UC, Razeghi O, Gould J, Sidhu BS, Sieniewicz B, et al. A rule-
373		based method for predicting the electrical activation of the heart with cardiac
374		resynchronization therapy from non-invasive clinical data. Med Image Anal Elsevier
375		B.V.; 2019; 57 :197–213.
376	14.	Karoui A, Bear L, Migerditichan P, Zemzemi N. Evaluation of Fifteen Algorithms for
377		the Resolution of the Electrocardiography Imaging Inverse Problem Using ex-vivo and
378		in-silico Data. Front Physiol 2018;9.
379	15.	Duchateau J, Sacher F, Pambrun T, Derval N, Chamorro-Servent J, Denis A, et al.
380		Performance and limitations of noninvasive cardiac activation mapping. Heart Rhythm
381		2019; 16 :435–42.
382	16.	Bear LR, Huntjens PR, Walton RD, Bernus O, Coronel R, Dubois R. Cardiac electrical
383		dyssynchrony is accurately detected by noninvasive electrocardiographic imaging.
384		Heart Rhythm Elsevier Inc.; 2018;15:1058–69.
385	17.	Niederer SA, Lumens J, Trayanova NA. Computational models in cardiology. Nat Rev
386		<i>Cardiol</i> Springer US; 2018; 16 :100–11.
387	18.	Duchateau J, Potse M, Dubois R. Spatially Coherent Activation Maps for
388		Electrocardiographic Imaging. IEEE Trans Biomed Eng 2017;64:1149-56.
389	19.	Gold MR, Singh JP, Ellenbogen KA, Yu Y, Wold N, Meyer TE, et al. Interventricular
390		Electrical Delay Is Predictive of Response to Cardiac Resynchronization Therapy.
391		JACC Clin Electrophysiol 2016;2:438–47.
392		
393		

394 Tables

Patient ID	Sex	Age [y]	Scar	ECG	QRSd [ms]	TST [ms]	TAT [ms]	
1	F	72	No	LBBB, SR	139	39	30	
2	М	69	No	LBBB, AF	179	59	59	
3	М	79	Yes (8)	IVCD, SR	138	3	3	
4	М	57	Yes (6)	IVCD, SR	126	14	14	
5	F	68	No	LBBB, SR	185	69	69	
6	М	53	No	LBBB, SR	165	50	50	
7	F	67	No	LBBB, SR, AVB1	156	72	72	
8	М	68	No	LBBB, SR	154	54	54	
9	М	73	Yes (1)	LBBB, SR, AVB1	176	77	77	
10	М	84	No	LBBB, SR, AVB1	180	50	50	
11	М	69	No	LBBB, SR, AVB1	170	68	68	
	73% M	69±8.7	27% Yes	82% LBBB	160.7±18.81	50.45±22.6	49.6±24.3	

395 Table 1: Characteristics of the patients.

396

Statistics are reported in the last row as average ± standard deviation for numerical data and
as percentage for categorical data. Abbreviations: QRSd, QRS complex duration; TST, transseptal time; TAT, total activation time; LBBB, left bundle branch block; SR, sinus rhythm;
AVB1; atrioventricular block first degree; IVCD, intraventricular conduction delay.

402 Table 2: Correlation between electroanatomic maps (EAMs) and reconstructed activation

times for all points in the LV and RV endocardium and LV epicardium in all patients.

Patient ID	LV endo	LV epi	RV endo	Overall
1	0.953	_	—	0.953
2	0.903		—	0.903
3	0.327		—	0.327
4	0.777		_	0.777
5	0.885	0.966	0.735	0.805
6	0.765	0.863	0.188	0.797
7	0.751	0.863	0.496	0.788
8	0.893	0.952	0.509	0.878
9	0.942	0.932	0.323	0.817
10	0.914	0.949	0.759	0.840
11	0.720	0.782	—	0.831
Overall	0.833	0.677	0.576	0.816

404

ID	Ι	П	ш	V1	V2	V3	V4	V5	V6	aVF	aVL	aVR	all
1	0.941	0.886	0.918	0.979	0.947	0.972	0.863	0.375	0.889	0.852	0.935	0.939	0.934
2	0.191	0.920	0.928	0.849	0.885	0.991	0.949	0.754	-0.364	0.934	0.905	0.572	0.881
3	0.966	0.861	0.979	0.951	0.934	0.983	0.986	0.978	-0.301	0.958	0.984	0.432	0.944
4	0.707	0.969	0.961	0.975	0.995	0.993	0.989	0.882	0.973	0.971	0.916	0.940	0.978
5	0.899	0.623	0.879	0.968	0.996	0.986	0.981	0.469	0.646	0.799	0.919	0.630	0.963
6	0.979	0.959	0.938	0.978	0.990	0.984	0.914	0.853	0.907	0.847	0.971	0.978	0.981
7	0.800	0.591	0.935	0.964	0.991	0.940	0.930	0.759	0.246	0.852	0.942	0.341	0.843
8	0.908	0.732	0.914	0.979	0.961	0.988	0.985	0.981	0.941	0.869	0.937	-0.002	0.935
9	0.872	0.819	-0.687	0.967	0.937	0.982	0.975	0.817	0.306	0.518	0.081	0.864	0.917
10	0.870	0.858	0.418	0.941	0.953	0.946	0.622	0.767	0.905	0.622	0.819	0.878	0.932
11	0.918	0.930	0.666	0.981	0.978	0.956	0.877	-0.198	0.840	0.892	0.846	0.931	0.940
all	0.855	0.845	0.833	0.923	0.956	0.940	0.936	0.687	0.555	0.830	0.852	0.842	0.923

Table 3: Correlation between recorded and fitted ECG, grouped by patient and lead.

408 Figure captions

- 409 Figure 1 (Summary of the method). The workflow starts with the CMR acquisition of the
- anatomy of the heart and the torso (with electrode positions) and the standard 12-lead ECG
- (blue box). In the pre-processing phase (yellow box), a 3D anatomy of the patient is
- reconstructed from CMR/CT sequences. The parameter identification phase (light green box)
- aims at fitting the parameters of the model (CVs and EASs), to minimize the difference
- between recorded and simulated ECG. The reconstructed activation map was eventually
- 415 validated against invasive EAM (dashed light blue box).
- 416 Figure 2 (Illustrative reconstruction). Example of the activation reconstruction for patient #4.
- 417 A: recorded (blue) and fitted (orange) ECG. B: 3D view of the activation map with collected
- 418 EAM points. C: LV bull's-eye plot (scar in purple.)
- 419 Figure 3 (Validation against invasive mapping). Bull's-eye plots for each patient showing the
- 420 EAR (blue) and LAR (red) in the LV. The solid-colored regions refer to the recorded maps,
- 421 while the hatched-colored regions are the reconstructed ones. Scar is in purple. BPs are
- 422 marked by stars.





