# Non-Invasive Electrogram Estimation from Body Surface Potential Mapping using Artificial Intelligence

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**Abstract**

*In this study, we propose a novel approach utilizing 3D Convolutional Neural Networks (CNNs) to estimate atrial electrical activity from Body Surface Potential Mapping (BSPM). The data used consists of a database comprising 16,800 simulations that encompass both sinus and ectopic beats, generated using a cellular automata model and diverse atrial geometries derived from a statistical shape model. Our method involves converting BSPM into 2D for each time instant as input for a CNN and outputting the corresponding 2D images of the electrical estimations in the heart. To evaluate the performance of our approach, we compared it with the traditional Tikhonov 0 order regularization method. Our results demonstrate that the proposed CNN-based method outperforms the traditional approach, surpassing it by 0.87±0.05 vs. 0.73±0.05 for average EGM correlation and 0.04±0.01 vs. 0.07±0.01 for root mean squared error, achieving more accurate estimations of atrial electrical activity. These results highlight the effectiveness of deep learning methodologies, particularly 3D CNNs, in accurately estimating electrical activity from BSPM, without relying on detailed cardiac geometry or location information, and aiming to improve the current state-of-the-art electrocardiographic imaging solved by Tikhonov regularization.*

## 1. Introduction

Electrocardiographic imaging (ECGI) has emerged as a valuable tool in non-invasive cardiac imaging, allowing for the reconstruction of cardiac electrograms (EGM) from Body Surface Potential Mapping (BSPM). However, traditional ECGI methods often face challenges related to the ill-posed nature of the inverse problem of electrocardiography and the requirement for precise patient geometry segmentation [1]. These limitations can compromise the quality and accuracy of ECGI signals, impeding its widespread adoption in clinical practice.

In response to the limitations of traditional ECGI methods, our study introduces a novel approach utilizing a Convolutional Neural Network (CNN) autoencoder to estimate EGMs directly from BSPM signals. By circumventing the need for precise patient geometry segmentation and location, our approach aims to overcome the challenges associated with traditional ECGI methods and improve the accuracy and robustness of cardiac electrogram reconstruction.

The main objective is to assess the accuracy and reliability of the 3D CNN in estimating cardiac electrograms from BSPMs and compare its performance with traditional Tikhonov regularization methods in simulated scenarios.

Additionally, we seek to evaluate the performance of both methods under geometrical uncertainties.

## 2. Methods

### 2.1. Database

For this study, a comprehensive database of cardiac and torso geometries was used. This database counted with 42 different atria from real patients that were processed to maintain node correspondence. Related to torsos, 16,800 different geometries were obtained from a Statistical Shape Model (SSM), also establishing node correspondence between torsos. For each atria, 400 simulations of both sinus and ectopic beats were generated using an automata-based framework [2]. Each propagation was generated with different initial conditions, leading a total of 16,800 different simulations, ensuring a comprehensive representation of atrial electrical patterns.

In order to account for inter-patient variability in heart position, for each simulation a different cardiac location and orientation inside the torso was considered. To set the position, the cardiac geometry parted from the center of the chest and was randomly rotated in a range of [-20º, 20º] and displaced in a range of [-20, 20] mm if the rotation in any axis surpassed the 80% of the limits defined (above 16º), and [-35, 35] mm on the contrary, to achieve physiological locations.

Once a different position was defined for each simulation, the forward problem was computed using the Boundary Element Method (BEM), obtaining the BSPM propagation in the corresponding torso. To avoid the inverse crime, each BSPM had a gaussian noise addition with a signal to noise ratio (SNR) set randomly between the ranges of [0, 3, 6, 10, 15, 20] dB and then filtered using a low pass filter of 40 Hz.

As the objective of the study was to compare the performance of the neural network versus traditional ECGI, EGMs of each case were estimated by solving the inverse problem of electrocardiography using zero-order Tikhonov regularization and L-curve optimization [3].

Prior to neural network development, BSPMs were comprised in 2D images at each time instant by selecting a total of 128 nodes that represent the electrode vest distribution from ACORYS MAPPING SYSTEM (Corify Care, SL, Spain), and setting them into a 2D format. Original simulated EGMs were also transformed into volumetric images to facilitate spatial and temporal feature extraction. These data underwent temporal and amplitude normalization to standardize intensities and mitigate noise, ensuring consistency across simulations and enhancing the robustness of subsequent analyses.

### 2.2. Neural Network Architecture

An asymmetric 3D-CNN autoencoder model was developed to estimate EGM signals from BSPM signals. BSPM images with dimensions of 9x18x76 were used as input, while output EGM images had dimensions of 65x65x76 (Fig. 1). The CNN encoder consisted of 4 convolutional layers, and the decoder comprised 7 layers, facilitating feature extraction and spatial hierarchies. Throughout the model, Rectified Linear Unit (ReLU) activation function was employed, except for the output layer, which utilized a sigmoid function. To capture temporal dependencies and contextual information more effectively, a Long Short-Term Memory (LSTM) [4] layer was integrated into the decoder, resulting in superior reconstruction quality. Max pooling and upsampling layers were incorporated to handle variations in data sizes, while batch normalization and dropout layers were strategically inserted to improve model generalization and mitigate overfitting.

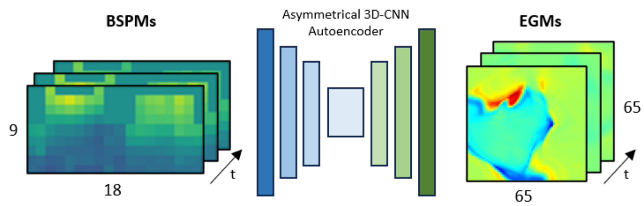


Fig. 1. Neural Network Architecture.

### 2.3. Analysis of the results

Training and validation of the CNN model were conducted using different subsets of the constructed database, in which 11,200 simulations were selected for the training set and 2,800 for the validation set, ensuring simulations of different cardiac geometries were used for each subset. A variant of the stochastic gradient descent with momentum was employed for optimization (Adam optimizer [5]), while hyperparameters were fine-tuned through grid search techniques to maximize model performance.

Evaluation of model performance was conducted on a separate test set of another different 2,800 simulations, by comparing original signals, Tikhonov regularization solutions, and model predictions. Evaluation metrics, including correlation coefficient (CC) and root mean squared error (RMSE), were employed to measure similarity and accuracy between the original signals and the respective solutions and predictions.

For this study two scenarios were considered. In the first scenario, the solutions analyzed were calculated knowing the cardiac geometry and position, while in the second one, geometrical uncertainty was considered by computing Tikhonov regularization for a different transfer matrix calculated with the same torso but a different atria geometry and heart position, simulating a more realistic scenario in which a priori this information is unknown.

## 3. Results

### 3.1. Comparison with geometrical knowledge

Predictions from the 3D-CNN autoencoder demonstrate better estimation of EGM morphology and amplitude compared to classical ECGI. The network yielded an improvement on EGM correlation over Tikhonov regularization: 0.87±0.05 vs. 0.73±0.05 and RMSE: 0.04±0.01 vs. 0.07±0.01 as shown in Fig. 2.A.

Matching the CC and RMSE results, when the late activation times (LATs) were calculated, higher accuracy was observed in the maps predicted with the neural network, showing a greater focalization of the earliest activation site than with the classical method (Fig. 2.B).

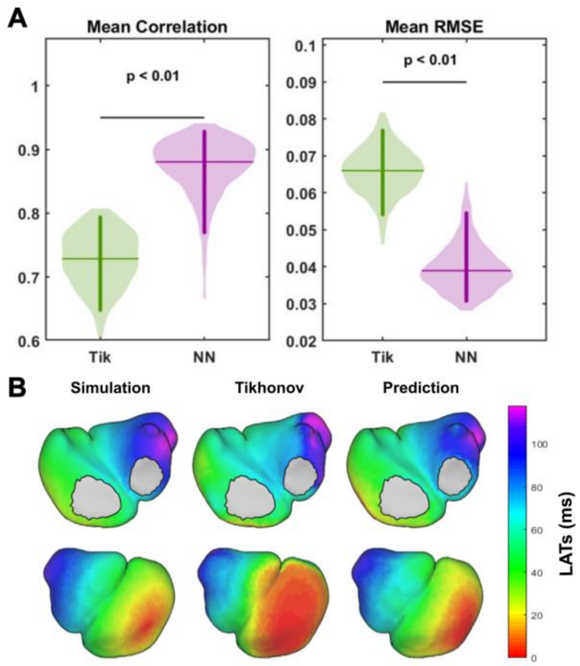


Fig. 2. **A** - Violin Plots of mean CC and mean RMSE between the estimations obtained by computing classical ECGI (green) and the predictions with the CNN (purple) when cardiac geometry and position are known. **B** - LATs maps comparison obtained with the original simulation, the EGMs computed with classical ECGI and the CNN estimation.

Related to EGMs, a sample is illustrated in Fig. 3. It can be observed that EGMs were less over-smoothed in our CNN prediction as compared with Tikhonov resolution, obtaining an enhanced recovery of EGM morphology and amplitude.

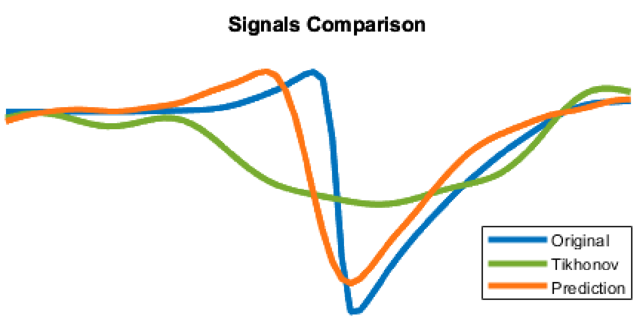


Fig. 3. Electrogram comparison on a single node, in which (blue) is the original signal of the simulation, (green) the Tikhonov estimation and (orange) the CNN prediction.

### 3.2. Comparison with geometrical uncertainties

In this case, the proposed autoencoder showed the same results obtained in the first study (a correlation of 0.87±0.05 and RMSE of 0.04±0.01) as the CNN input only depends on the BSPM, while classical ECGI suffered a drop in correlation of 0.31±0.16 and in RMSE of 0.09±0.01 (Fig. 4.A). This scenario highlights the superior performance of our CNN model in capturing the underlying electrical activity of the heart as it is not affected by cardiac geometrical uncertainties (Fig. 4.B).

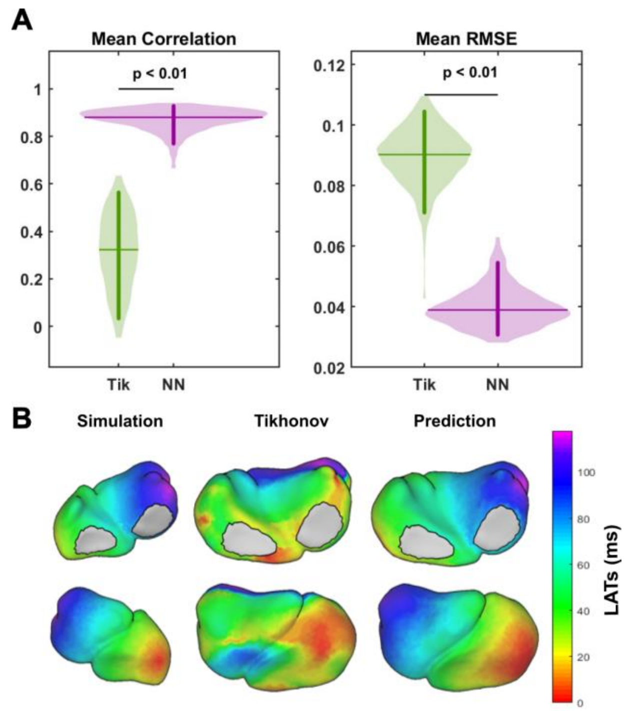


Fig. 3. **A** - Violin Plots of mean CC and mean RMSE between the estimations obtained by computing classical ECGI (green) and the predictions obtained with the CNN (purple) when cardiac geometry and position are unknown. **B** - LATs maps comparison obtained with the original simulation, the EGMs computed with classical ECGI and the CNN estimation. In this case the cardiac geometry used in estimations differs from the original simulation as there is geometrical uncertainty.

## 4. Discussion

Our study demonstrates the capability of artificial intelligence to reconstruct EGMs from BSPM signals, without relying on detailed cardiac geometry or location information. By introducing an asymmetrical CNN autoencoder model, we showcase enhanced accuracy in estimating atrial electrical activity, offering promising advancements for ECGI in clinical practice.

These findings underscore the effectiveness of our CNN-based methodology in improving the recovery of electrogram morphology and amplitude, surpassing traditional ECGI methods that are often compromised due to the ill-posed nature of the inverse problem of electrocardiography and the need for precise patient geometry segmentation.

The success of our CNN model can be attributed to its ability to effectively leverage the spatial and temporal information inherent in BSPM data processed as 2D images, which allows capturing complex spatial relationships and temporal dynamics.

Despite these advancements, it is essential to acknowledge the limitations of our study, including the need for further validation on clinical datasets to assess its generalizability and real-world applicability, and ongoing efforts to optimize model architecture and training strategies.

## 5. Conclusion

Our study represents a significant step forward in cardiac electrophysiology, offering promising implications for the diagnosis and management of cardiac arrhythmias. By pushing the boundaries of ECGI technology and reducing error metrics, our approach holds potential to enhance patient care and advance the field of cardiovascular medicine towards personalized, real-time cardiac healthcare.

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## Conflict of Interest

A.M. Climent and M.S. Guillem are co-founders and stakeholders of Corify Care S.L. R. Molero and E. Zacur receive honoraria form Corify Care S.L.

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