CT-Scan Free Neural Network-Based Reconstruction of Heart Surface Potentials From ECG Recordings

Kamil Bujnarowski[1], Pietro Bonizzi[1], Matthijs Cluitmans[2], Ralf Peeters[1], Joel Karel[1]

[1]Department of Data Science and Knowledge Engineering, Maastricht University, The Netherlands
[2]Department of Cardiology, Cardiovascular Research Institute Maastricht, Maastricht University, The Netherlands

Abstract

The inverse problem in electrocardiography concerns mapping electrical activity measured on the surface of the body back onto the heart in a non-invasive way. With the use of CT-scans and mathematical/geometric models of the human body, it is possible to translate body surface recording into epicardial potentials which provide advanced diagnostic information of the heart activity that a standard ECG or BSPM is unable to, especially for specific heart conditions such as arrhythmia. An encoder-decoder structure is proposed as an approach which encodes body surface potentials into latent representations before using them as input to be decoded into epicardial potentials without the use of geometric information obtained from a CT-scan. Using data from an ECG-Imaging experiment performed on dogs [1], a proof of concept is created by predicting the general wave-forms of 98 heart surface electrodes based on 168 body electrodes. The neural network manages to reconstruct the heart surface potentials with a mean square error of $0.332mV \pm 0.442$ *on the training set and* $0.763mV \pm 0.336$ *on the testing set.*

1. Introduction

ECG-Imaging (ECGI) [2] can be used to map the electrical activity measured on the body surface back onto the heart in a non-invasive way. It is a powerful tool that provides diagnostic information about the electrical activity of the heart, which is directly visualized at the heart level, yielding details that ECG or BSPM procedures are not able to provide [3], especially for arrhythmias [1, 4]. Typically this is done using ECG measurements on the body surface, and mathematical and geometric models of the heart and torso with corresponding electrode positions, to determine the electrical source and propagation of electricity through mediums between the heart and the surface where measurements are taken [1, 3, 5]. The problem can be stated using the following formula: $\Phi_B(t) = A\Phi_H(t)$,where $\Phi_B(t)$ are the body surface potentials at time t, $\Phi_H(t)$ the heart surface potentials at time t and A the transfer matrix from heart to body surfaces as determined by CT-scans and geometric models. However CT scans imply a certain level of radiation, and is a procedure which may not be available as an option for all patients [4]. Using a CT-scan-free machine learning model trained on ECG or BSPM to reconstruct the corresponding heart surface potentials could serve as a preliminary study of a patient's condition before more thorough examination is performed. The mathematical and geometric models used in ECGI could be learned by a neural network in order to provide similar diagnostic information without the need of a CT scan, and the costs and complexity of just an ECG procedure. The aim of this research was to explore the usefulness of time-series reconstruction using deep learning to arrive at a reconstruction of electrical activity on the heart surface from surface ECG measurements. The main approach is an encoder-decoder type neural network which learns to encode standard ECG systems into a compressed latent representation. This latent vector is then used as input to the decoder network for predicting the heart surface readings. A dataset of simultaneous body surface and epicardial surface potentials measured on dogs [1] was used as a proof of concept for the tasks presented here. The main findings of this study show that a neural network is able to learn a latent representation of cardiac electrical activity on the body surface and decode some morphology onto the heart surface, showing that there is potential in using deep learning for this purpose. However, given the limitations, particularly in the dataset used, this can only serve as a proof of concept until validation can be performed.

2. Methodology

2.1. Data

The dataset, previously used in [1], contains multiple procedures recorded on 4 different dogs with 160-200 electrodes on the body and around 100 on a strip placed on the

 ISSN: 2325-887X DOI: 10.22489/CinC.2020.200

heart surface. This investigation conformed to the Guide for the Care and Use of Laboratory Animals published by the U.S. National Institutes of Health (National Institutes of Health Publication 85-23, revised 1996). Animal handling was in accordance with the European Directive for the Protection of Vertebrate Animals Used for Experimental and Other Scientific Purposes (86/609/EU) and was approved by the institutional review committee for animal studies. Body potentials were recorded at 2048Hz sampling frequency while the heart electrodes were sampled at 1000Hz. In total 93 beats were isolated and matched between heart and body potentials over a time period of approximately 1 second. This data contained many bad signals or missing electrodes and the matrices of electric potential over time contained different amounts of electrodes. Hence, it could not be assumed that they were consistent with each other. In order to be able to construct input tensors for a neural network, it was decided to use only the data of the first dog. The resulting dataset contained only 6 matched beats of BSPM recordings using 168 body electrodes and heart surface recordings from 98 heart electrodes. Heart surface potentials were re-sampled to 2048Hz.

All recordings are normalized to a range $[-1, 1]$ to make sure all are within the same scale. A rolling window of 512 points (approximately quarter second of recordings) is applied over the electrode systems. Using a stride of 1 ensures that the dataset has sufficient amount of samples and that the neural network is trained on windows where the wave form appears at multiple positions, not limited to the left or right ends. Since only 6 matched beats were usable for the first dog, the first 5 were used for training and the final one for testing.

2.2. Neural Network Architectures

The main approach for neural network based ECGI was to use the latent representations, learned by an autoencoder, and decode the information stored inside into heart surface potentials. Body surface recordings are passed through the encoder component of the network to produce vectors of size $[32, 1]$. The vector is then used as input to a second network which scales the vector up into the dimensions of the heart surface recordings, essentially decoding it. Inside the network, the hidden layers consist of 5 convolution layers with 16 filters each. 5 layers provided an adequate reduction in dimensionality of the input before reaching the dense layers. 16 kernels were experimentally determined to be sufficient. The kernels apply convolution in the time dimension only and no information about the spatial relations between the electrodes is used. A kernel size of $(5, 1)$ is chosen for this purpose. Furthermore, each convolution layer is followed by a max-pooling layer with a stride of $(2, 1)$ to reduce dimensionality in the time domain. Since the max-pooling layer outputs a tensor smaller by a factor of 2 in the time domain, the original window size during pre-processing is kept in powers of 2. The convolution layers are followed by a fully connected layer with 32 nodes before leading into the latent layer, once again containing 32 fully connected nodes. The layers following the latent layer are mirrored, forming the encoder-decoder structure. All layers use ReLU activation functions [6], to deal with vanishing gradient problem, except the final output layer which has a tanh activation to map to range $[-1, 1]$. The encoder and decoder networks are not part of the same model and were trained separately. It is expected that using latent representations of ECGs would help the model generalize to other patients/procedures better than a direct network trained on predicting the heart surface straight from the body surface.

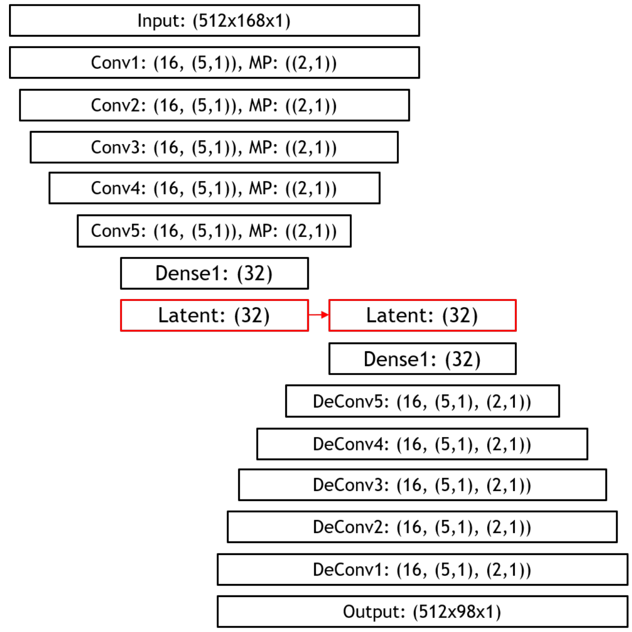

Figure 1. Architecture of LeNet style decoder neural network for predicting heart potentials.

3. Analyses and Results

Each system of body potentials was encoded using the autoencoder from Figure 1, providing latent representations in 32 values. These vectors and their corresponding matched beats on the epicardium were then used to train a decoder to predict dog's heart potentials. Results for one paced beat can be seen in Figure 2 for training data and Figure 3 for test data which show the prediction of heart surface potentials after 100 epochs of training against the ground truth signals. Both mean square error (MSE) and average Pearson correlation over the electrodes were measured on all windows, with MSE $0.332 \pm 0.442mV$ and mean correlation 0.19 ± 0.17 on the training set and MSE $0.763 \pm 0.336mV$ and mean correlation 0.11 ± 0.10 on the test set. These correlations are low, comparable at most to reconstruction using 3-electrodes performed in [1]. However, the more accurately reconstructed windows, as can be observed in Figures 2 and 3, have comparable morphologies to those from [1] where the mean correlation was 0.60 when using a similar amount of electrodes.

3.1. Discussion

The encoder-decoder structure is able to generate latent representations of dog body surface potentials which could then be used to predict corresponding heart surface potentials. As seen in Figure 2, the training set is predicted without significant phase-lag. The pacing spike is left included to give clearer indication of when the system struggles, showing that the correct magnitude is not always reconstructed. The test window in Figure 3 still contains relevant differences in parts of the wave-forms. Errors seem to be concentrated in reconstructing correct magnitudes and elements that are not consistent throughout the dataset. However, the general structures and patterns are present. The conclusions that can be drawn from this are that there is potential in performing neural network based ECGI, and with a proper dataset there is enough information in the electrode systems to train a model for this task. The results of this study can only serve as a proof of concept for assessing the proposed approach, as can be seen by the high variance in correlations in both training and testing sets. More research is necessary to investigate how well these methods work on data recorded on human subjects rather than dogs and especially to what extent are the results generalizable. However, the results suggest that, until a model with sufficient data is trained that can handle the slight variations between individual heart beats, the autoencoder ought to be re-trained for each patient.

4. Conclusion

This report has proposed a machine learning approach to solving the inverse problem in electrocardiography by using a neural network to predict epicardial potentials based on input ECG recordings. The methods included an autoencoder trained to encode latent representations of the ECG systems such that these representations contain all the relevant information required to map the measurements onto the heart surface. Using data from procedures performed on dogs [1] to train the autoencoder, the model mapped the encoded latent representations of body potential systems to the heart surface. Although still containing relevant morphological differences in the testing windows, this method shows promise in reconstructing the wave-forms and some of the characteristic features of the heart potential signals such as QRS complexes and T waves, and their duration. It can be concluded that a neural network is able to learn a latent representation of dog body surface potentials which can be used to reconstruct the cardiac electrical activity to solve the inverse problem without the need of a CT-scan.

Although a limitation of this study is the use of invasive data, the potential to omit the CT scan in the future is worth investigating. Additional research is required to investigate these methods in electrocardiography, including an appropriate dataset with matched body and heart surfaces. This research serves as a proof of concept for predicting epicardial electrical potential based on latent representations of ECG recording on the body surface. Hopefully it will lead to further advances in this field of machine learning based electrocardiography to make it more available and reliable.

References

[1] Cluitmans MJ, Bonizzi P, Karel JM, Das M, Kietselaer BL, de Jong MM, Prinzen FW, Peeters RL, Westra RL, Volders PG. In vivo validation of electrocardiographic imaging. JACC Clinical Electrophysiology 2017;3(3):232–242.

[2] Cluitmans MJM, Peeters R, Westra R, Volders P. Noninvasive reconstruction of cardiac electrical activity: update on current methods, applications and challenges. Netherlands Heart Journal 2015;23(6):301–311.

[3] Intini A, Goldstein RN, Jia P, Ramanathan C, Ryu K, Giannattasio B, Gilkeson R, Stambler BS, Brugada P, Stevenson WG, et al. Electrocardiographic imaging (ecgi), a novel diagnostic modality used for mapping of focal left ventricular tachycardia in a young athlete. Heart Rhythm 2005; 2(11):1250–1252.

[4] Ramanathan C, Ghanem RN, Jia P, Ryu K, Rudy Y. Noninvasive electrocardiographic imaging for cardiac electrophysiology and arrhythmia. Nature medicine 2004;10(4):422–428.

[5] Wang Y, Cuculich PS, Zhang J, Desouza KA, Vijayakumar R, Chen J, Faddis MN, Lindsay BD, Smith TW, Rudy Y. Noninvasive electroanatomic mapping of human ventricular arrhythmias with electrocardiographic imaging. Science translational medicine 2011;3(98):98ra84–98ra84.

[6] Agarap AF. Deep learning using rectified linear units (relu). arXiv preprint arXiv180308375 2018;.

Address for correspondence:

Kamil Bujnarowski
Grote Gracht 58 C03, 6211SX Maastricht, Netherlands
k.bujnarowski@student.maastrichtuniversity.nl

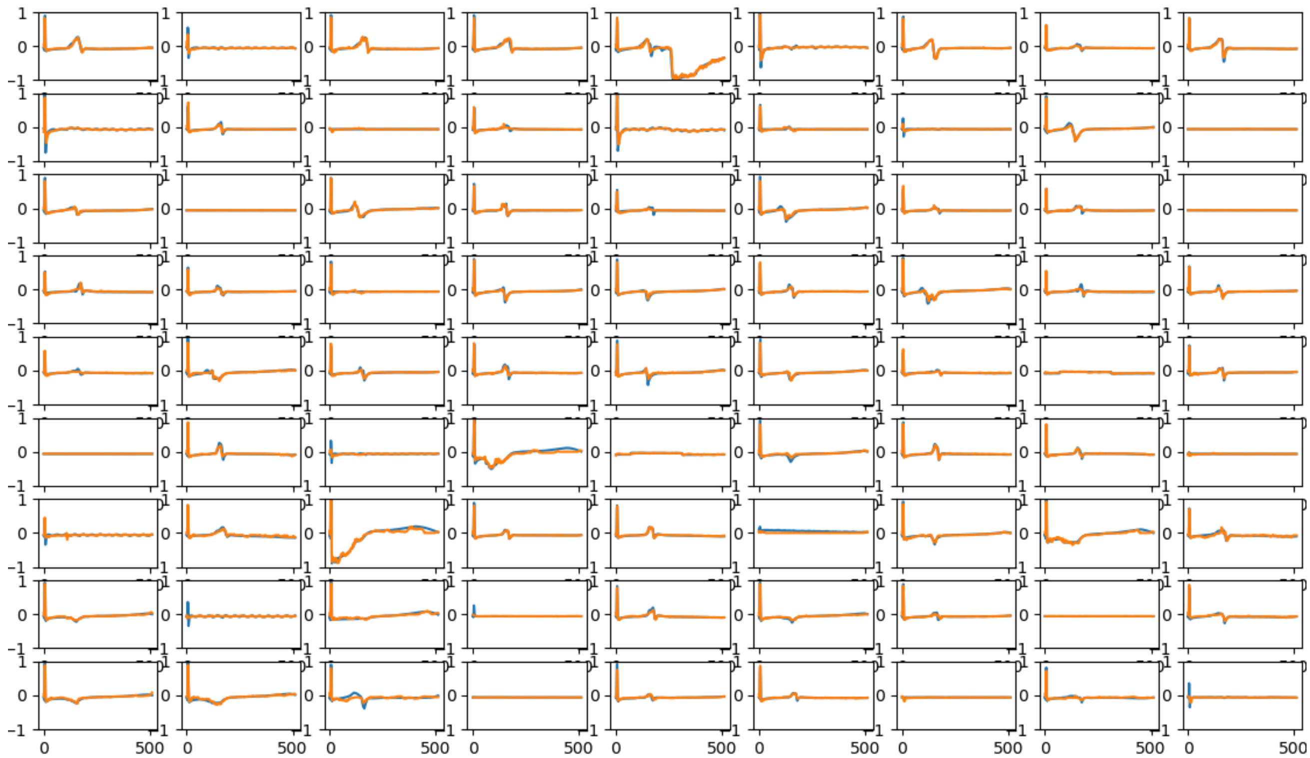

Figure 2. Dog heart potentials sample for 81 of 98 leads, ground truth signal (blue) plotted against decoder network reconstruction (orange) for dog data the network was trained on. MSE: 0.073, Correlation: 0.42.

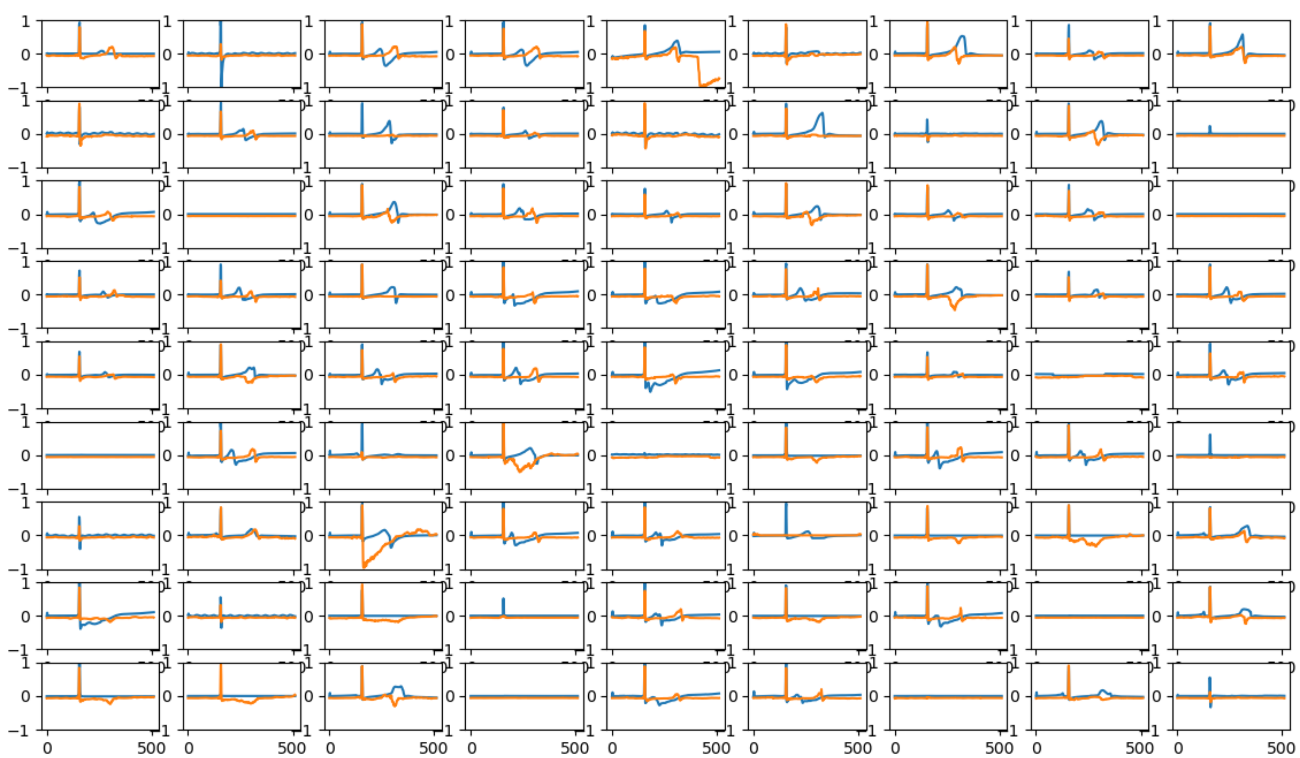

Figure 3. Dog heart potentials sample for 81 of 98 leads, ground truth signal (blue) plotted against decoder network reconstruction (orange) for dog data the network was not trained on. MSE: 0.580, Correlation: 0.28.