Similarity Prediction of Intracardiac Electrograms Images Using Regression Model Based on Siamese Network Architecture

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Abstract

Pace mapping allows accurate localizing of the source of cardiac arrhythmia when the arrhythmia is non-inducible during the electrophysiological study. It compares the electrocardiographic (ECG) morphology of clinical ventricular tachycardia (VT) with the paced one. Often intracardiac electrograms (EGMs) from implantable cardiac devices are the only source of ECG morphology. However, when presented as images by programmer devices, EGM can only be assessed for similarity by subjective eyeballing.

This study aimed to develop regression models for objectively measuring similarities between images of two distinct signals.

Six regression models based on Siamese neural network architecture with two types of custom similarity layers were trained on 40,000 pairs of augmented images from 17,421 digital intracardiac EGMs.

The best performance showed the model with Efficientnet_b0 as the backbone for Manhattan similarity (MSE = 0,002, R2 = 0.98) and Resnet18 as the backbone for Pearson correlation (MSE = 0,009, R2 = 0.973). All models showed better prediction accuracy for Manhattan similarity (MSE_{mean}=0.002) as compared to Pearson correlation (MSE_{mean}=0.011).

Regression models based on the Siamese network architecture with custom similarity layers provide a promising tool for objectively measuring the similarity of EGM images acquired from implanted devices.

1. Introduction

Ventricular tachycardia (VT) and ventricular fibrillation (VF) are two heart rhythm disorders that can cause sudden cardiac death. The implantable cardioverter defibrillator (ICD) is a common therapy for arrhythmias, automatically detecting and treating life-threatening heart rhythms. Radiofrequency (RF) ablation is another effective therapy for reducing arrhythmic events. One technique for identifying the origin of VT/VF during catheter ablation is pace mapping, which uses controlled electrical stimuli to reproduce the 12-lead surface ECG beat morphology recorded during VT. However, patients with ICDs don't usually have their ECG recorded during out-of-hospital VT episodes, so the only electrophysiological information available is from intra-cardiac electrograms (EGM) recorded by the ICD. The ICD programmer interface doesn't allow access to digital EGM, so similarity assessment can only be done by eyeballing images of EGMs. The purpose of this study is to develop regression models to objectively measure similarities between images of distinct EGM signals stored in ICD to improve arrhythmia mapping precision.

2. Methods

2.1. Framework of the MatcherNet

The purpose of MatcherNet is an objective prediction of the similarity of two EGMs given in the form of images. We applied transfer learning using relatively small pre-trained CNN of three different types: 1) Resnet18, 2) EfficientNet B0, and 3) MobileNet B2. Based on these backbones the Siamese neural network was constructed using the images of two signals as inputs (224x224). Feature extraction was performed by propagating the images through the backbones. These two feature vectors (1x64) were forwarded into the similarity layer to predict the similarity score by one of the following methods, widely used in the clinical electrophysiological mapping systems: 1) Pearson correlation coefficient $\in$[-1; 1] and 2) Manhattan similarity score $\in$[0; 1] (the formulas are represented in Figure C, D).

2.2. Dataset and pre-processing

For the supervised learning, we created training and validation datasets using 17400 digital intracardiac EGMs exported from the electrophysiological station and plotted as grayscale images. The pairs of images were randomly assigned to each other pairwise, and the similarity scores were calculated using digital signals corresponding to them and further utilized as labels. The training (90%) and validation (10%) datasets consisted of the 40000 pairs with a uniform distribution of similarity scores. The images were augmented randomly with respect to negative inversion, ECG paper, marks, background opacity, rotation, and smoothing (Figure 1A).

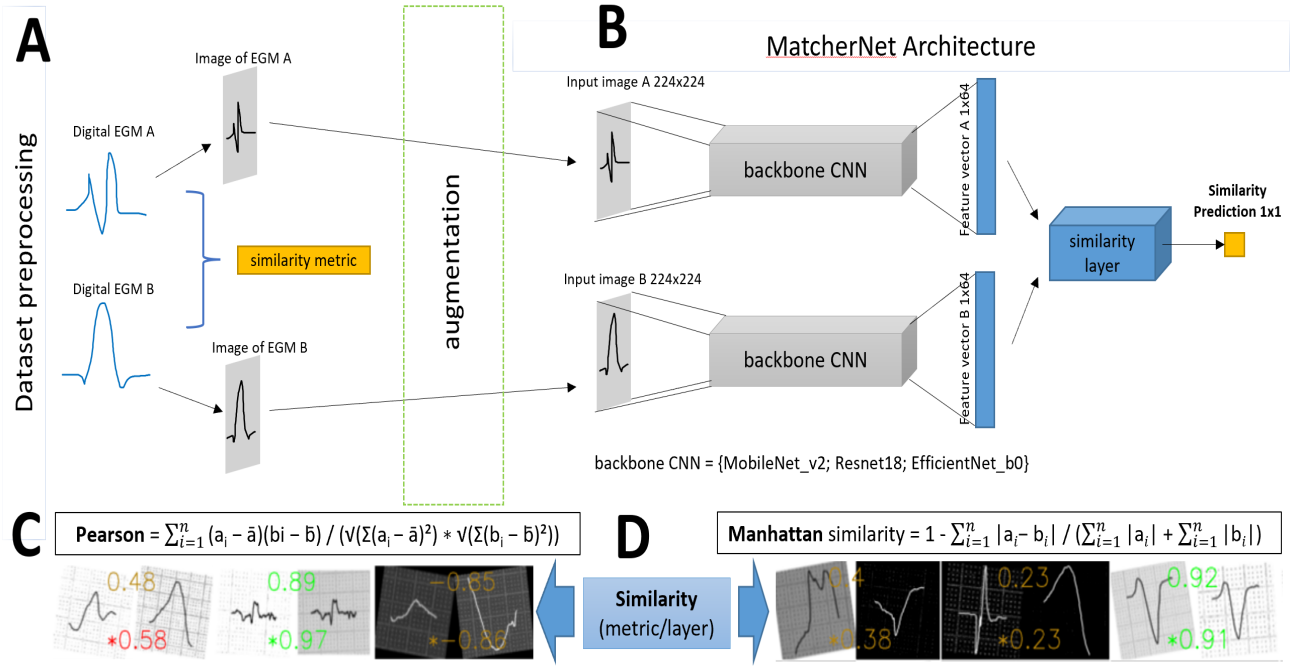

Figure 1. Siamese neural network "MatcherNet".
A: The data processing, where two 1D signals are used for similarity calculation and transformed into their 2D images with further augmentation.
B: The architecture of MatcherNet, which takes two 2D EGM images as input into backbones and outputs feature vectors. The feature vectors are then processed in the similarity layer, which produces a similarity score as the final output. The initial similarity calculated with 1D signals is used as a label for backpropagation during training.
C and D: Examples of similarity prediction between pairs of intracardiac electrogram (EGM) images using Pearson coefficient (C) or Manhattan similarity (D). The pairs of EGM images are represented by 2D images generated from their corresponding 1D signals. The predicted similarity score between each pair is shown at the top, and labels are calculated using digital signals at the bottom of each pair of images as numerical values.

2.3. Experiment process

We constructed six regression models based on MatcherNet architecture, using Resnet18, Efficientnet_b0, and MobileNet_V2 as backbones and two types of custom similarity layers were used: Pearson correlation coefficient and Manhattan similarity. The training was performed in 100 epochs with a learning rate of 0.001 and batch size of 64.

2.4. Model evaluation

Using the same method as for the training dataset, we created the test dataset consisting of 1000 pairs of images and similarity scores as labels, created from another set of 8000 EGMs. MSE and R2 scores were used as performance metrics for the evaluation of the models.

3.Results

After the tuning of hyperparameters, convergence was achieved in all six models (Figure 2). The performance metrics are presented in Table 1.

Table 1. MatcherNet performance metrics.

Similarity metric/backbone	MSE	R2
Pearson correlation		
- Resnet18	**0.01**	**0.97**
- Efficientnet_b0	**0.09**	**0.973**
- Mobilenet_v2	**0.014**	**0.957**
Manhattan similarity	**0.002**	**0.98**
- Resnet18	**0.002**	**0.98**
- Efficientnet_b0	**0.002**	**0.972**
- Mobilenet_v2	**0.003**	**0.958**

Performance of six configurations of MatcherNet Siamese Network for Pearson correlation and Manhattan similarity with 3 different backbones. MSE: mean square error, R2 value: coefficient of determination.

The best performance showed the model with Efficientnet_b0 as the backbone for Manhattan similarity (MSE = 0,002, R2 = 0.98) and Resnet18 as the backbone for Pearson correlation (MSE = 0,009, R2 = 0.973). All

models showed better prediction accuracy for Manhattan similarity (MSEmean=0.002) as compared to Pearson correlation (MSEmean=0.011).

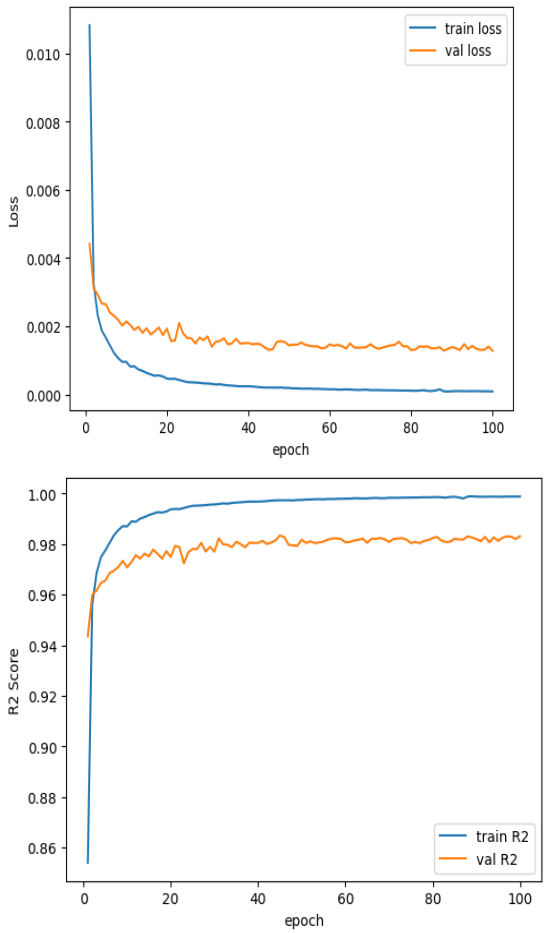

Figure 2. Loss function and R2 score for the MatcherNet based on ResNet18 backbone.

4. Discussion

EGMs stored in the ICD devices in patients experiencing life-threatening VT may play an important role in the identification of the origin of heart rhythm disorder[1]–[5]. They are especially helpful in cases when clinical tachycardia is not inducible during the electrophysiological study. In such situations, pace mapping could be performed by electrical stimulation from different sites of the ventricular myocardium, and the morphology of stimulated EGM acquired at ICD-electrode can be matched to the EGM of the clinical episodes. In clinical practice, this approach is limited by the fact that digital signals of implanted devices cannot be accessed or exported. Rather, their images are displayed on the programmer [6][4]. Therefore, the assessment of similarity between EGMs has to be performed by eyeballing. The objective measurement of similarity between the EGM signals during pace mapping is of great importance [7], [8], [9]. Our study provides a promising tool for objectively measuring the similarity of EGM images acquired from implanted devices. The developed regression models based on the Siamese network architecture with custom similarity layers showed high prediction accuracy both for Manhattan similarity and Pearson correlation coefficient. The best performance was achieved by the model with Efficientnet_b0 as the backbone for Manhattan similarity and Resnet18 as the backbone for Pearson correlation.

Possible implementation in clinical practice. The following clinical case provides some insight how the model can support clinical practice: a patient with ischemic cardiomyopathy suffered multiple syncope and ICD shocks due to recurrent ventricular fibrillation VF episodes triggered by monomorphic premature ventricular contraction (Figure *3*A). Pace mapping from different sites of the left ventricle was performed with an assessment of similarity between EGM of clinical VF-trigger retrieved from ICD and EGMs acquired from ICD during stimulation from mapping catheter. RF ablation was successfully conducted in the area with the maximal Manhattan similarity score between pacing-induced EGMs and clinical EGM-pattern. (Figure 3B). In the follow-up, the patient was free from VF episodes.

Overall, the developed regression models based on the Siamese neural network architecture with custom similarity layers can accurately predict the similarity of EGM images. Future studies should explore the benefit of these models for clinical applications, such as improving the accuracy of arrhythmia mapping in patients with implantable cardiac devices.

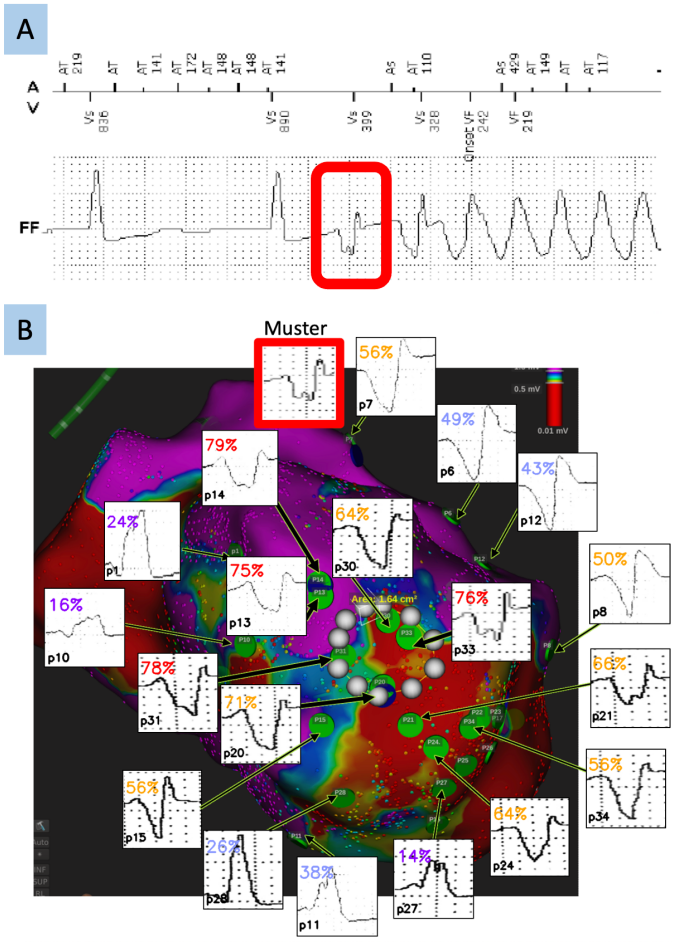

Figure 3. Example of clinical implementation of the model. A: Clinical episode of ventricular fibrillation triggered by ventricular extrasystole (highlighted by the red frame). EGM acquired from ICD during trigger activity is stored as a template. B: Pace mapping from 34 sites in the left ventricle using Manhattan similarity prediction. The region with the maximal similarity score was targeted for ablation.

5. Conclusion

Regression models based on the Siamese network architecture with custom similarity layers provide a promising tool for objectively measuring the similarity of EGM images acquired from implanted devices. The model can support pace mapping to find the origin of clinical ventricular arrhythmia precisely.

6. References

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