Phase Mapping for Cardiac Unipolar Electrograms with Neural Network Instead of Phase Transformation

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Abstract—A phase mapping is an approach to processing signals of electrograms that are recorded from the surface of cardiac tissue. The main concept of the phase mapping is an application of the phase transformation with the aim to obtain signals with useful properties. In our study, we propose to use a simple sawtooth signal instead of a phase of a signal for processing of electrogram data and building of the phase maps. We denote transformation that can provide this signal as a phase-like transformation (PLT). PLT defined via a convolutional neural network that is trained on a dataset from computer models of cardiac tissue electrophysiology. The proposed approaches were validated on data from the detailed personalized model of the human torso electrophysiology. This paper includes visualization of the phase map based on PLT and shows the applicability of the proposed approaches in the analysis of the complex non-stationary periodic activity of the excitable cardiac tissue.

Index Terms—digital signal processing, neural network, convolutional neural network, unipolar electrogram, cardiac mapping, phase mapping, cardiology, electrophysiological study

I. INTRODUCTION

A unipolar electrogram is a popular method for invasive electrophysiological studies in cardio-surgery [1]. Cardiac mapping is a modern extension of a unipolar electrogram analysis that presents cardiac electrophysiology in the format of maps or video maps.

The most complex processing is required for the presentation of the periodic and non-stationary periodic activity of myocardium (cardiac muscle tissue). This activity usually observed during the ventricular tachycardia or atrial flutter. A phase mapping is the most common approach for processing of such type of data. These approaches were widely used in biological in vitro experiments [2]–[4], and lately was translated to clinical practice [5]–[7].

The phase mapping approach includes two parts. The first part is the phase transformation of the signals that are recorded from several leads, and the second part is an interpolation and spatial analysis of all phase signals (see Fig. 1). The phase transformation usually based on a shift in time or Hilbert transform [7]. Also, several alternative approaches were proposed [5].

Here, we are aiming to replace the phase transformation on the more robust approach. We propose to use a sawtooth signal with [0,1] range of values. These signals should have breaks that related to depolarization of transmembrane potential in cardiomyocytes in point of measurements. Between two depolarizations, the signal should linearly decrease from 1 to 0 value. Fig. 2 shows the proposed signal and its relationship with the cardiomyocyte transmembrane potential.

This signal should be obtained from unipolar electrogram with some transformation. We named this transformation as the phase-like transformation (PLT). In contradiction to previously proposed approaches [2]–[7] we do not define this transformation as series of mathematical operations (see Fig. 1 (B1)). We define the PLT via training of neural network on series of simple 1D model of myocardial electrophysiology (see Fig. 1 (B2)).

For proof-of-concept, we test the proposed idea with the more complex and detailed model of the human heart electrophysiology.

II. METHODS

In this study, a simple 1D model of the myocardium provides a series of action potentials. These action potentials converted to unipolar signals with a simple equation. Obtained signals separated into the training and validation dataset. Then,
the neural network is trained on these datasets. The complex
and realistic model of the human torso electrophysiology
provides action potentials and extracellular potential, and
the last one is very close to the real unipolar signals. Extracellular
potentials are processed with the neural network for build
phase maps based on the PLT transformation. In the end, these
maps are compared with true electrophysiological activity
in the myocardium that is shown via a map of the action
potentials from the realistic model in a fixed point in time.

Idealized 1D models of myocardial tissue were computed
with the monodomain equation. The 1D strand contained 1024
points, and the activation point was located in 128 nodes from
one side of the strands. TNNP06 [8] described electrophysiolo-
gical activity of ventricular cardiomyocytes respectively.

Unipolar electrograms from 1D strand were obtained with
the following formula [9]:

$$
\phi(x') = -\kappa \int_x \frac{\partial V}{\partial x} \cdot \frac{1}{\sqrt{(x-x')^2 + h^2}} dx,
$$

where $V$ is the transmembrane potential in point $x$, $\phi$ is an
extracellular potential or signal from a unipolar catheter, $h$ is
the height of the catheter above the 1D strand, and $x'$ is an
electrode position.

The coefficient $\kappa$ and a voltage in absolute physical values
are not important for our study because we normalized results
using the division of each signal to their maximal absolute
amplitude.

Training and validation datasets were generated with a vari-
ation of the following 1D model parameters: the stimulation
frequency ($FR = \{2000, 1000, 500, 300, 200\}$ Hz), conduc-
tion velocity ($CV = \{10, 20, 40, 80\}$). Parameters of the
cardiomyocytes in the 1D strand were taken from the original
article [8] without changes. Also, the following parameters
of the (1) equation were variated: height of electrode over
the strand ($h = \{5, 10, 20, 50, 80\}$) and position of electrode
along the strand ($x' = \{448, 512, 640\}$). As shown in Fig.
3, used ranges of parameter variation provide significantly
different signals for analysis and cover all possible signal
shapes, available from the real recordings.

PLT signals for training were generated from action po-
tential using a 0 mV threshold level as criteria for the
depolarization phase (break of the function). Examples of PTL
signals are shown in Fig. 3. Thus, the full datasets of simple
model results contained 300 signals with 4096 ms lengths
and 1000 Hz frequency of discretization. The training and
validation datasets respectively contain 150 (50%) and 150
(50%) signals.

The test dataset was generated by a detailed personalized
finite element model of two ventricles and the torso. Model
geometry was based on computed tomography data of one
patient. The torso includes regions of the heart, lungs, blood in
heart chambers, and spinal cord. Each torso region had realistic
conductivity, according to [10]. The heart included realistic
conduction anisotropy that was introduced with a rule-based
approach and realistic heterogeneity of current transmembrane
densities [11]. The TNNP06 model [8] performed a realistic
simulation of cardiomyocytes electrophysiology. A bidomain
model with bath described excitation wave propagation and the
torso electrophysiology. We initiate a spiral wave using the
S1S2 protocol to provide the realistic extracellular potential
for ventricular arrhythmia of the reentry type. Each point of
the heart surface mesh provides one signal for the test dataset.
Thus, the entire model provides 34354 signals with 4096 ms
length.

The described approach is one of the most realistic ways
for the simulation of electrophysiology in both ventricles and
the torso. In particular, this approach correctly includes the
far-field effect. The used model was verified against clinical
data of electrocardiography with 224 leads during activation
of the myocardium from a point [12]. We suppose that model
complexity and a wide representation of physiological features
make the model suitable for the generation of the test dataset.
This dataset was used only with the neural network that is
trained to process the signals from the ventricular myocardium.

Convolutional neural network for processing was adapted
III. RESULTS

The model of cardiac tissue provides a set of excitation waves for a normal healthy myocardium (Fig. 3 (A-B)) and additionally provides cases with alternance of action potentials (Fig. 3 (D-F)). The last ones appeared under high stimulation frequency at the 1D strand.

Idealized models provide a set of unipolar electrograms with significant differences between cases. The majority of signals were similar to clinically observed electrophysiological behaviour for sino-atrial rhythm (Fig. 3 (A, C), [1]), flutter or fibrillation (Fig. 3 (B, D–F), [14]). However, some signals look atypical, and we suppose that the dataset covers both real and unobtainable cases of electrogram signals.

### TABLE I

| Metrics of Neural Network Performance at 150 Epoch. Mean Absolute Error (MAE), Mean Square Error (MSE). |
|-------------------------------|-----------------|-----------------|-----------------|
| Num. of cases | Ventricles | MAE | MSE |
|-----------------|-----------------|-----------------|-----------------|
| Train (1D) | 150 | 0.0250 | 0.0021 |
| Validation (1D) | 150 | 0.0327 | 0.0024 |
| Test (3D) | 34354 | 0.0888 | 0.0266 |

NN training requires 100+ epochs for reaching of a loss plateau. Table I shows the training process and the final value of the loss, respectively. We manually analyzed shapes of the sawtooth signals and counted a number of wrongly detected action potential upstrokes in the validation dataset. Only 10 out of 859 (1.16%) upstrokes were incorrectly identified.

Qualitative analysis of NN outputs is presented in Fig. 3. NN perfectly processes any periodic signals and the major part of non-stationary periodic signals (see Fig. 3 (A–E)). However, the model makes an error with some non-stationary periodic signals that contain double peaks with close placement (see Fig. 3 (F)). The model cannot reach zero levels in zones from the U-Net architecture for biomedical image segmentation [13]. Fig. 4 presents our modifications. The size of all convolution kernels was replaced from 3x3 to 3x1 elements. The size of the pooling and up-sampling layers was replaced from 2x2 to 4x1 with an aim to increase the perception field of NN. The number of neurons in all layers was proportionally increased for the processing of input vectors with 4096 elements. Also, we add Dropout (30%) and Gaussian noise layer (mean=0, std.=0.2) after the U-Net narrow layer for improving NN robustness. The loss function was a sum of the mean absolute error and mean squared error with equal weights. We used the ADAM method of optimization with learning rate reduction on the plateau of validation loss. The NN process unipolar signals from windows with 4096 values and provides a PLT signal as an output with 4096 values.
without electrophysiological activity and in the ends of the sawtooth shapes.

The result of the NN application on the realistic personalized model of human electrophysiology is presented in Fig. 5. As can be seen, the obtained quality of the phase map clearly reveals the rotor core and the front of the excitation waves. However, the value of the mean absolute error metric here is at three and half times higher than the ones for 1D strand models (see Table I).

IV. DISCUSSION AND CONCLUSION

In our study, we propose phase-like transformation (PLT) for processing unipolar electrograms and the method of its definition via the convolutional neural network that is trained on a set of generated data from the numerical experiments.

The proposed transformation provides signals with desirable properties as we planned in the beginning. It can reveal complex non-stationary periodic behavior in the myocardium and is applicable for the building of phase maps (see Fig. 5).

Our approach to transformation definition significantly differs from the method that was proposed before. It does not require a manual choice of signal transformations and filters with good basic properties. Instead of that, they require proper choice and tuning of several models of the physiological process. Loss functions here are a direct way for assessment of the algorithm able to process complex data.

We suppose that the proposed approach has a wide area of application. It may be applied to the processing of unipolar electrograms from the unipolar catheter, multi-leads catheter, and balloons, microelectrode arrays, invasive and non-invasive systems of cardiac mapping [15], [16].

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