An Electrophysiological Cardiac Model with Applications to Ischemia Detection and Infarction Localization

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Abstract

A novel electrophysiological cardiac model is introduced in this paper. The proposed cardiac model considers six key regions that characterize the cardiac electrical activity. This allows the model to solve the forward and inverse electrocardiology problems in near real time. The proposed cardiac model is used as a basis for two near real time clinical diagnostic applications. The first is the detection of myocardial ischemia. The second is the localization of myocardial infarction. These diagnostic methods use the proposed forward and inverse problem solutions and machine learning approaches to diagnose automatically, noninvasively, and accurately these two serious heart conditions. Moreover, the proposed diagnostic methods have high true positive and negative accuracies suitable to be used in clinical expert systems. The accuracies for the ischemia detection and infarction localization methods are 91% and 68.57%, respectively.

1. Introduction

Most cardiac modeling methods focus on simulating the chemical dynamics of the cardiac cells using nonlinear coupled differential equations. To set up the forward and inverse problems, these methods simultaneously model more than 100,000 cells or attempt to solve Maxwell's equations using numerical methods such as finite element and finite difference techniques[1, 2]. This complexity requires high computational time. Additionally, such methods require a geometrical representation of the heart and body torso for each individual. Both the computational complexity and dependency on the cardiac and body geometry makes them inadequate for developing near real time diagnostic methods.

Current literature divides the cardiac modeling problem into three problems: modeling the electrical activity of the cells and tissue and solving the inverse or forward problems. Most of the current cardiac cell models are based on the Hodgkin and Huxley model including the Lou-Rudy models, Noble models, and all those who followed. Moreover, current modeling approaches that solve the cardiac modeling problem require having a geometric model of the heart and torso of the patient and a model of the cells and tissue to solve for the forward and inverse problems. Generally, Lagrangian interpolation in one-, two-, and three-dimensions, and cubic Hermite basis functions are used in geometric modeling[3].

In this work, we take a different approach in developing patient independent solutions for the forward and inverse electrocardiology problems in comparison to the traditional solutions. While the problem addressed in this work is still the modeling of the cardiac electrical system, the modeling occurs at a higher physiological level. Here, the cardiac modeling problem is divided into two sub-problems. The first is to model the action potentials of the cardiac regions. The second is to define the interaction between the cardiac electrical subsystems and their measured output at the body surface.

The approach presented in this paper models the generation of the ECG signal using a solution for the inverse problem and forward problem. The modeling approach is based on cardiac electrophysiology, where the ECG signal is generated from the modeling of the sinoatrial (SA) node, atrioventricular AV node, Bundle branches (Bb), Purkinje fibers (Pf), and left and right ventricles (LV and RV) walls. The electrical activity of each of these components of the heart is estimated by the difference of two sigmoid functions. The model has the ability to characterize the P wave, PR segment changes, QRS complex, ST segment changes, and T wave.

Two clinical applications are examined using the automatic diagnostic methods presented here. The first is the detection of myocardial ischemia. The second is the localization of myocardial infarction.

The importance of the two diagnostic methods can be seen in the potential impact on early screening of myocardial ischemia and on quickly identifying the location of myocardial infarction. As noted by the World Health Organization, ischemic heart disease is the leading cause of death in the world with almost 7.2 million fatalities per year [4]. The proposed diagnostic method can be used in the early screening of myocardial

ischemia. Early screening of myocardial ischemia is proven to help prevent heart attacks [5].

2. Data sets

Two datasets are used in this work:

1. The Long-Term ST Database consisting of 86 digitized long-term (Holter) ECG tape recordings, mostly from subjects who had transient myocardial ischemia. This dataset is used for the detection of myocardial ischemia.
2. The PTB Diagnostic ECG Database containing 549 records from 294 subjects. The records are digitized at 1 KHz per signal. Most of the records are from patients who had myocardial infarction. This dataset is used for the localization of infarcts in the 4 cardiac regions

A ten-fold cross validation is used to validate the diagnostic and localization algorithms. The ten fold cross validation is described as follows: Divide data into 10 set of size n/10, called folds, train on 9 sets and test on 1 set, repeat the process 10 times and store the diagnostic results, and finally combine the results and calculate the overall accuracy. The ten fold cross validation test ensures that the training and testing sets are patient independent.

3. Methods

The motivation for this modeling approach starts from the observation of the electric potential of a cardiac cell and specific groups of cells during the cardiac cycle. To further clarify, consider the hypothesis that the heart can be represented by a vector of N electrical regions (make the equation font identical to the rest of the paper. It looks to big.)

$$Heart = \left[region_1 \quad region_2 \quad \ldots \quad region_N \right] \quad (1)$$

In this case, the cardiac modeling sub-problem is to determine the function ϕ that represents the action potentials at the cardiac regions $\phi(region_1)$, $\phi(region_2)$, ..., $\phi(region_n)$. The aim of the second sub-problem is to determine the functions f and f^{-1} described in equations (2) and (3), respectively:

$$f\left(\left[\phi(region_1) \quad \phi(region_2) \quad \ldots \quad \phi(region_n)\right]\right) = ECG, \quad (2)$$

$$\left[\phi(region_1) \quad \phi(region_2) \quad \ldots \quad \phi(region_n)\right] = f^{-1}(ECG). \quad (3)$$

Equation (2) describes the forward problem as the function, f, that generates the ECG from the electrical activity at the cardiac regions $(region_1, region_2, ..., region_n)$. Equation (3) represents the inverse problem as the function f^{-1} that estimates the cardiac electrical activity from measured ECGs.

One of the difficulties of the cardiac modeling problem is that as stated in (2) and (3), the solution is not uniquely defined. This is seen in (2) and (3) as the number of unknown parameters is greater than that of known parameters. This work addresses this difficulty by considering a finite number of regions, constraining the activity of each region to the cardiac electrophysiology, and using least squares optimization. We have found the cardiac electrical cycle of the selected regions is well modeled by the difference of two sigmoids, which is defined by

$$\phi(t, a_1, c_1, a_2, c_2, k) = k\left(\frac{1}{1-e^{a_1(t-c_1)}} - \frac{1}{1-e^{a_2(t-c_2)}}\right) \quad (4)$$

where k represents the magnitude of the wave, a_1 and a_2 control the rising slope, and c_1 and c_2 control the translation in the direction of the t axis as shown in Figure 1.

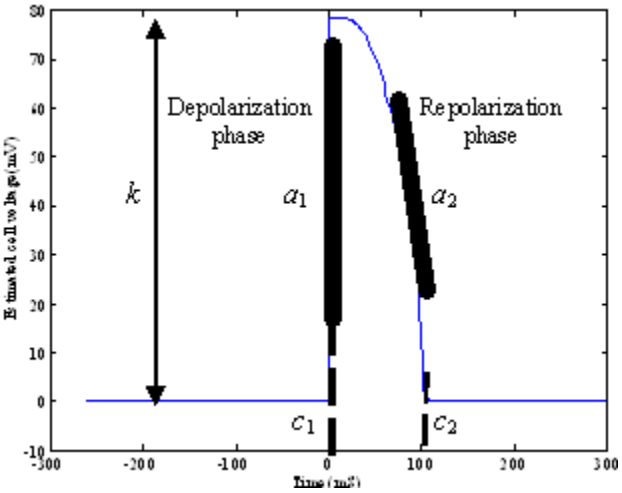

Figure 1: Proposed heart cell activity

By representing the delay of the region activity arriving at the positive and negative electrodes of the leads as ϕ_i^+ and ϕ_i^-, where

$$\phi^+ = \phi\left(t, a_1, c_1 + \delta_1^+, a_2, c_2 + \delta_2^+, k\right) \quad (5)$$

$$\phi^- = \phi\left(t, a_1, c_1 + \delta_1^-, a_2, c_2 + \delta_2^-, k\right), \quad (6)$$

where δ_1^+ and δ_1^- represent the activation delay at the positive and negative electrodes, respectively. The δ_2^+ and δ_2^- represent the delay of the deactivation timing at the positive and negative electrodes, respectively.

The following sections describe the forward and inverse problem solutions, and the clinical applications of this model.

3.1. Forward problem solution

By summing the potential difference of each region's activity at the positive and negative terminals of each

lead, the forward problem solution, i.e. the ECG signal at any lead are generated as:

$$\hat{f}_{ECG} = \sum_{i\in[SA,AV,Bb,Pf,Lv,Rv]} \left(\phi_i^+ - \phi_i^-\right), \quad (7)$$

where ϕ_i^+ and ϕ_i^- represent the cell group activity at the positive and negative electrodes for the SA node, AV node, bundle branches (*Bb*), Purkinje fibers (*Pf*), and left and right ventricles (*Lv* and *Rv*). $\hat{f}_{ECG}$ is the generated ECG signal.

3.2. Inverse problem solution

In order to determine the model parameters and solve the inverse problem, a constrained least squared minimization technique, lsqcurvefit provided by Matlab [6], is applied to the sum square error of the estimated ECG of (2) and actual ECG signals:

$$Error = \sum_{signal} \left(ECG - \hat{f}_{ECG}\right)^2, \quad (8)$$

Since the approach is applied to a single beat at a time, the beats are separated automatically using ECGPUWAVE [7]. The beginning and end of the atrial and ventricular activity are also generated from the ECGPUWAVE method.

In order to have an accurate match between the modeled and actual ECG signal, a template model with known parameter is used as an initial condition. The signal is matched with the direction of the R peak and the highest cross-correlation point between the two signals is chosen.

3.3. Ischemia detection

The proposed approach utilizes the decision tree training algorithm C4.5 [8] to generate a decision tree that classifies the condition of each beat. The estimated ECM parameters and the first fifty principle component analysis (PCA) components of the trimmed ECG signal starting from the R peak until the end of the T wave are used as attributes in the training process. The classes corresponding to the samples are ischemic or healthy.

3.4. Infarction localization

Similar to the ischemia detection method, a C4.5 decision tree is trained using the model parameters and the first fifty PCA components of the trimmed ECG signal starting from the R peak until the end of the T wave. The classification method is applied to leads: I, II, III, aVL, aVF, V_1, V_2, …, V_6 detecting if the ECG measured at those leads shows signs of infarctions. The results of the classification is either 1 for infarcted, or 0 for healthy. An automated method is used to localize infarcts based on the Selvester criteria [9]:

Table 1: ECG changes seen in acute myocardial infarction.

Area	Changes and leads
Anterior	V2- V4
Septal	V1 -V2
Lateral	I, aVL, and V5, and V6
Inferior	II, III, and aVF

4. Results

The proposed model is applied to signals from the LTST and PTB diagnostics database. The average error between the model generated ECG and an actual ECG is calculated to be less than 5%. The accuracies for the myocardial ischemia and localization of myocardial infarction are 91% and 68.57%, respectively.

4.1. ECG generation accuracy

The modelling approach is applied to healthy, ischemic, and infracted beats from the PTB diagnotics database and the LT-ST dabase. Figure 2 shows a randomly selected estimated signal from the LT-ST database. The percentage error for this signal was calculated to be less than 4% of the original signal, which is negligible in clinical measurements.This error is considered as the noise in the signal.

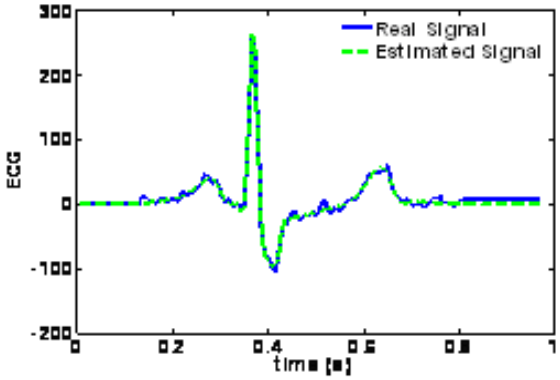

Figure 2: Original healthy and estimated clean signal.

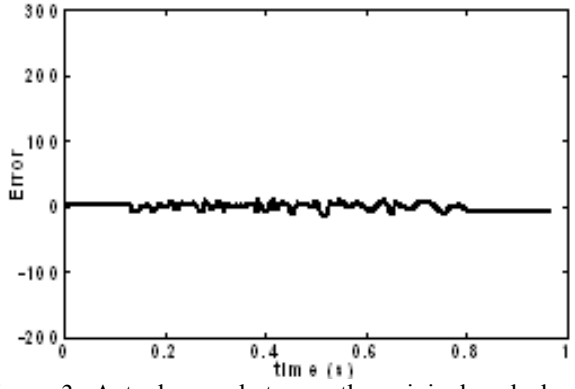

Figure 3: Actual error between the original and clean

signal

4.2. Ischemia detection experiment

The application of the model parameters and the PCA components of the signal as features for a C4.5 decision tree classifier yielded accuracy of 91.62% with sensitivity of 94.89% and sensitivity of 75.66%. The confusion matrix for the proposed approach can be seen in:

Table 2: Confusion matrix for the ischemia diagnostic method.

	Classified as	
	Ischemic	Healthy
Ischemic	16,035	828
Healthy	892	2,772

4.3. Infarction localization experiment

This section presents the results for the proposed infarction localization results. Similar to the ischemia detection experiment, a ten fold cross validation test is applied to the PTB diagnostics database. The results of applying the infarction localization approach to the PTB diagnostics database yielded an accuracy of 68.57%. The proposed ECM-PCA-Localizer is compared to the current best infarction localization technique, RPS/GMM approach, presented at the physionet/computers in cardiology 2007 in [10] as shown in:

Table 3: Comparison between the proposed and RPS/GMM method.

Approach	Accuracy
Proposed	68.57%
RPS/GMM	58.74%

5. Discussion and conclusions

As a summary, the results for the proposed ischemia detection and the infarction localization methods applied to the LT-ST and PTB diagnostics databases, respectively. Both approaches show excellent results when diagnosing ischemic and healthy beats, and localizing infarcts. The proposed diagnostic and localization methods use the ECM parameters obtained from the inverse problem solution.

The importance in the proposed model, ECM, is that it can be related back to the heart's physical and electrical activity. It can be seen that the parameters of the ECM can be used in the detection of ischemic and healthy heart beats. This is due to the fact that the model parameters captured the information regarding the cardiac regions and their effect on the ECG waves and segments, such as slope, interval duration, magnitude and segment's variation. Although as single lead model is presented, this model has been extended to account for multiple leads, with similar results.

The training processes for these diagnostic techniques are performed offline. The classification/diagnostic process is performed online. The waiting time for this diagnostic method is the inverse problem solution, which as presented in the previous chapter takes 10s. Therefore, these diagnostic methods can run in near real time.

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