A HEART CELL GROUP MODEL FOR THE IDENTIFICATION OF MYOCARDIAL ISCHEMIA

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Abstract: Due to the increasing prices of medical care, and especially due to cardiovascular injury; scientists are looking for inexpensive and less invasive ways to diagnose myocardial ischemia. Many studies have shown that the variations of the ST-segment in the ECG signal are an indicator for ischemia. For this purpose, this work proposes an approach based on a heart cell group model and principle component analysis, using a decision tree classifier to differentiate between the ischemic and healthy beats. The cardiac based model is based on a physiological model of the electrical cycle of depolarization and repolarization of the atria and ventricles. The model parameters are estimated by minimizing the squared error between the generated signal and the recorded ECG. The approach is applied to beats from the Long-Term ST database, which consists of 86 subjects and more than 20,000 beats in which 80% of the beats are ischemic and 20% are healthy. A 10-fold cross validation test is performed over the dataset. The accuracy of this approach is 91.62%, with sensitivity of 95.09% and specificity of 75.66%.

1 INTRODUCTION

Ischemic heart disease is the leading cause of death in the world with almost 14% of all deaths (AHA 2005) Moreover, the average number of individuals who undergo a heart attack as a result of myocardial ischemia in the United States is approximately 1.5 million cases, of which 500,000 are fatal (AHA 2005). Myocardial ischemia is defined as the deprivation of oxygen in some portions of the cardiac tissue due to a blockage in the coronary artery. If the deprivation continues for an extended period, the effected cardiac tissue will die; thus, leading to a heart attack. Tissue that has died is no longer functional and diminishes the mechanical pumping function of the heart (Pardee 1920).

Early detection of ischemia is crucial because, in most cases, the effects of myocardial ischemia are reversible if detected early enough (Long 1980). General screening of patients is vital to preventing myocardial infarction, since ischemia can be present without exhibiting symptoms.

This work proposes a cardiac based model, Principle Component Analysis (PCA) and a C4.5 decision tree classifier for the detection of myocardial ischemia. The cardiac model is based on a physiological model of the electrical cycle of depolarization and repolarization of the atria and ventricles. The Sinoatrial (SA) node, the Atrioventricular (AV) node, bundle branches, Purkinje fibers, and left and right ventricles are modelled as signal generators. The ECG is generated by the difference in signal amplitudes arriving at the positive and negative terminals of an ECG lead. The model parameters are estimated through the minimization of the squared error between the generated signal and the recorded ECG. In addition to the obtained model parameters, 50 of the components from applying PCA to the signal are used in the diagnosis. A C4.5 decision tree is then used as a classifier to determine if a beat is healthy or ischemic.

The purpose of using electrocardiogram signals for the diagnoses of myocardial ischemia is because it is one of the least expensive techniques available to physicians. Figure 1 shows a labelled ECG signal showing the P, Q, R, S, T waves, the ST segment and the J point. The use of the ST level in the detection of myocardial ischemia was hypothesized in 1920 (Pardee 1920). Examples of low cost methods are ST event alerts ($250 cost) and easy to administer) with sensitivity of 46% and specificity of 91% and exercise stress testing ($200-$300 cost) with 68% accuracy of 68% (R. Gianrossi 1989).

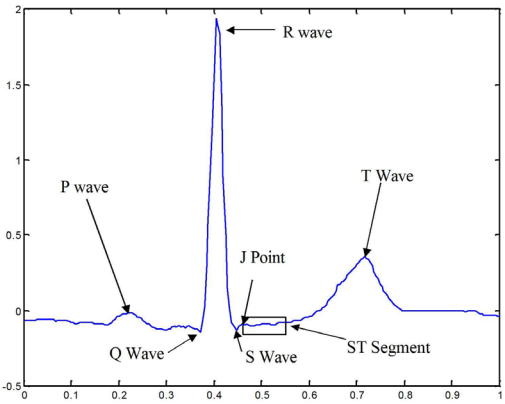

Figure 1: Labelled (ECG) signal.(Moody 2001).

Significant research has been undertaken to develop a more accurate, less invasive, and less expensive method for detecting myocardial ischemia. Much of this research focuses on the use of ECG signals. These methods build models or use thresholds of the ST deviation to determine if a patient's ECG signal might indicate ischemia.

Previous techniques that dealt with ischemia classification and detection when monitoring ECG signals started with low accuracy that increased significantly over time. These techniques are based on the hypothesis that myocardial ischemia can be detected by monitoring the ST variations.

Maglaveras et al. (N. Maglaveras 1994) have investigated a method for ischemia detection that uses supervised neural networks. The accuracy of this approach is of sensitivity of 73.0% and positive predictive accuracy of 69.5%.

RV Andreao et al. (R.V. Andreao 2004) employed a Hidden Markov Model for beat segmentation with the application of ischemia detection. The accuracy of this model is of sensitivity of 83.0% and positive predictive accuracy of 85%.

Additionally, T. Stamkopoulos et al. proposed an approach using nonlinear Principle Component Analysis (PCA) and neural networks in the identification of ischemic beats. The accuracy of this approach was 80% for healthy and 90% for ischemic beats when applied to the European ST-T Database (Stamkopoulos 1998).

Similarly, Victor-Emil Neagoe applied a Gaussian Neuro-Fuzzy Approach and PCA toward the classification of myocardial ischemia. The accuracy shown in the paper was 100% for 50 features. However, Neagoe dealt with only identifying ischemic and normal patients. Moreover, the number of training and testing data were 40 patients, half used for training and half for testing (Victor-Emil Neagoe 2003).

2 DATA SET AND PRE-PROCESSING

Various ECG and intracardiac datasets are available for the use of modelling and detecting myocardial ischemia. The data sets preserve the privacy of the subjects as there are no direct or indirect identifiers linking back to them.

2.1 Long Term ST Database

The Long-Term ST Database from PhysioNet contains 86 Holter ECG recordings from 80 independent patients. Holter recordings are ECG recordings recorded using portable recording devices, generally taken over a long period. These recordings were selected from the Holter libraries at Beth Israel Deaconess Medical Center in Boston, Physiolab (Laboratory of Biosignal Processing) of the Institute of Clinical Physiology in Pisa, Brigham and Womens Hospital in Boston, and the Zymed company. The recordings vary in length from 20 to 24 hours. Each record contains either two or three ECG leads. The records are digitized at 250 Hz with 12 bit resolution (Moody 2001).

Complete annotations have been provided for the database. These annotations label the significant ST shifts and episodes, the beginning (3-point) of most ST segments has been annotated along with R wave annotations using a 16 second averaging window. The beats were detected using WQRS function as part of the WFDB package supplied by the Physionet (Moody 2001).

To aid in the development of an ischemia classification algorithm, complete ST level annotations have also been provided. These annotations give the ST level, ST reference function, and the calculated ST deviation. The ST reference is expertly labelled moving average of the important ST shifts. The ST deviation is calculated by subtracting the ST level from the ST reference function shown in Figure 2 (Jager, Taddei & Moody 2003).

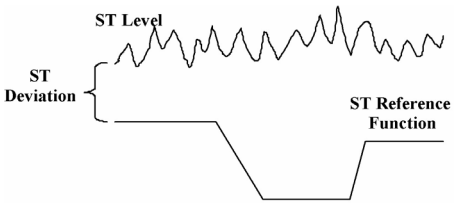

Figure 2: Example of ST deviation calculation.

The data consists of 43 free records from 42 patients and 43 fee records from 38 patients. The total number of beats used in this work is 20,528 for

both healthy and ischemic. The number of ischemic beats is 16,794, while that of the healthy beats is 3734.

In order to evaluate the proposed classifier, a ten fold cross validation is applied to the dataset. The ten fold cross validation is described as follows:

1. Divide data into 10 set of size n/10
2. Train on 9 sets and test on 1 set
3. Repeat the process 10 times and take the mean of the accuracy.

2.2 Signal Pre-processing

As mentioned in the previous section, the beats are obtained automatically from the records using the 'WQRS' function provided by the Physionet Toolkit. Each beat is then anchored such that the iso-electric line prior to the P wave is set to zero. A wavelet decomposition approach is used to denoise the signal from high frequency noise (GD. Clifford 2005).

3 METHOD

The classification approach utilizes a heart cell group model fitted to the patient's ECG signal along with the principle component analysis of the signal. The method is described in the block diagram shown in Figure 3.

A heart cell group model is used to generate a template ECG signal. Then, using a nonlinear constrained optimization technique, the model parameters are updated until reaching a certain error with the patient's signal beat. The estimated model fitting the ECG signal are then used with the PCA components as features in the C4.5 decision tree classifier.

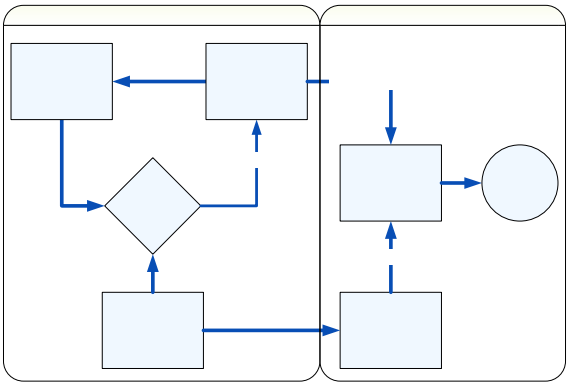

Figure 3: Block diagram of the Ischemia diagnosing method.

3.1 Heart Cell Group Model

Electrocardiograms indicate the electric activity of the heart over the body surface. In general, two types of model have been developed to characterize the ECG signal. The first type is a model used for interpolating experimental data and can be fitted to ECG signals without having a reference to the physical system. The second type is a model that can characterize the ECG signal and can be related back to the heart activity. The objective of this work is the latter modelling approach, focusing on development of a model that can estimate the activation sequences of the heart cells from real patient ECG signals. This objective is called the inverse problem. The difficulty of this problem is that unless it is stated in a particular manner, the solution will not be uniquely defined.

Several techniques have been employed for generating models to solve the forward and inverse problem. These techniques overcome the uniqueness problem by modelling the heart as a small number of moving dipoles. Some of these techniques apply the solution of Green's theorem (Method of Moments) or Multi-Pole technique to determine the scattering of the electric waves over the heart. These methods are considered accurate. However, the main drawback of these techniques is the computational complexity (Gulrajani 1998).

McSharry et al. presented a "dynamic ECG model" that incorporates the ECG features as a combination of Gaussian functions. Although this model is easy to build, it cannot be related to the heart cell activity (GD. Clifford 2005).

3.1.1 Proposed Cell Group Model

A Heart Cell Model (HCM) is proposed in this work based on the reconstruction of the ECG signal using a cell group model. This model accounts for the wave propagation of the SA node, the AV node, the bundle branches, Purkinje fibers, and left and right ventricles. We hypothesize that the electric activity of a heart cell group can be represented by a difference of two sigmoid functions.

The electric activity of the myocardial cells is caused by the variation of the positively and negatively charged ions of the cells. As presented by researchers (Andrew J. Pullan 2005), the electric activity of the cell is given in Figure 4 and it can be approximated by a difference of two sigmoid functions as shown in Figure 5.

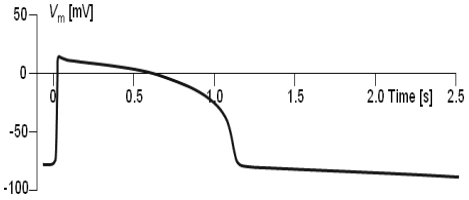

Figure 4: Conduction activity of the heart.

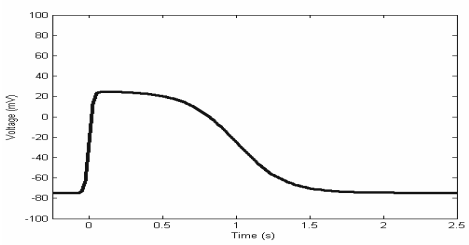

Figure 5: Proposed heart cell activity.

The cell group activity is modelled as the difference between two sigmoid functions:

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

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 *time* axis.

We hypothesize that the cumulative ECG signal is generated from the atrial and ventricular conduction activity. In this work, the P wave is assumed to be generated from the SA node activity; the PR interval from the AV node activity, and the QRS complex and T wave are generated from the activation of the bundle branches, the Purkinje fibers and, the right and left ventricles.

3.1.2 ECG Generation

As presented above, the ECG signal can be generated from the activation sequences of the heart cell groups. The same steps are used to generate the ECG from the modelled activation sequences. The model divides the heart into groups or nodes. Each node consists of a combination of cells at the SA node, the AV node, the bundle branches, the Purkinje fibers and, the right and left ventricles. Each node activation and deactivation sequence is represented as the difference between two sigmoid functions. The variables in the sigmoid functions consist of the magnitude, inflection (activation) point and the inclination slope. By summing the potential difference of the node signals at the positive and negative terminals of each lead, the ECG signal is generated:

$$\hat{f}_{ECG} = \sum_{i \in [SA, AV, Bb, Pf, LV, RV]} \left(f_i^+ - f_i^-\right), \quad (2)$$

where:

- SA and AV represent the activity of the SA and the AV node respectively.
- Bb and Pf represent the activity of the bundle branches and Purkinje fibers respectively
- LV and RV represent the activity of the Left and right ventricles respectively
- f^+ and f^- are the difference between two sigmoid functions as presented in (1) for each of the nodes at the positive and negative probes respectively

The following sections presents how the ECG wave features are generated. The features are the P wave, the PR segment, the Q wave, the R wave, and the S wave (QRS complex), ST segment, and T wave.

3.1.3 P Wave Generation

The P wave is generated from the potential difference between the electric conduction activity measured at the atrial cells at the positive and negative probes. In this approach, the atrial conduction activity at a single probe is estimated by equation (1). Moreover, it is hypothesized that the P wave can be generated from the conduction activity of the SA node:

$$P_{wave} = \left(f_{SA}^+ - f_{SA}^-\right), \quad (3)$$

The generation of the P wave using the difference of sigmoid estimation is shown in Figure 6.

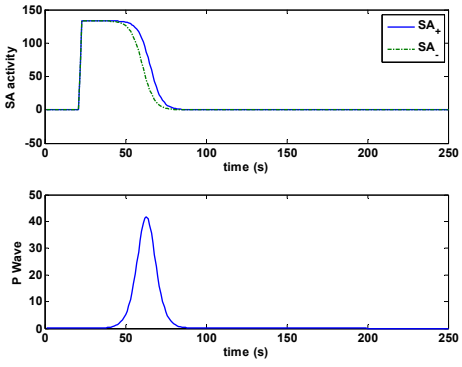

Figure 6: P wave generation using the differential sigmoid model.

3.1.4 PR Segment Generation

The PR segment occurs as the impulse travels from the AV node through the conducting tissue (bundle branches, and Purkinje fibers) towards the ventricles. Most of the delay in the PR segment occurs in the AV node. The PR segment is generally at the baseline; however, variations might occur due to certain heart diseases. Thus, by modelling the electric activity of the AV node as proposed in (1), and similar to the procedure shown in (3), we are able to generate the variations in the PR segment as shown in Figure 7.

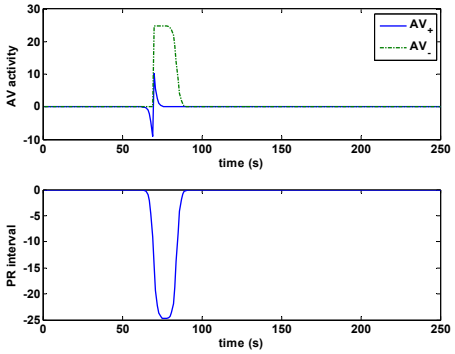

Figure 7: PR interval generation using the differential sigmoid model.

3.1.5 QRS Complex and T Wave Generation

The QRS complex and the T wave denote the interval for the beginning and end of the ventricular activation. When generating the QRS complex, the activity of the cell groups of the bundle branches, Purkinje fibers, and left and right ventricles are modelled during the ventricular cycle. The representation of the model for the QRS complex and T wave in an ECG signal is dependent on the difference between the positive and negative electrodes at the modelled cell groups. Figure 8 through Figure 10 show how each wave of the QRS complex and the T wave are generated using the differential sigmoid model.

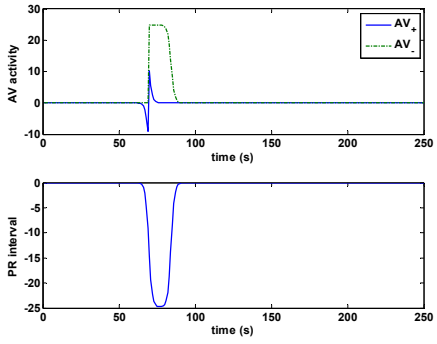

Figure 8: R wave and T wave generation.

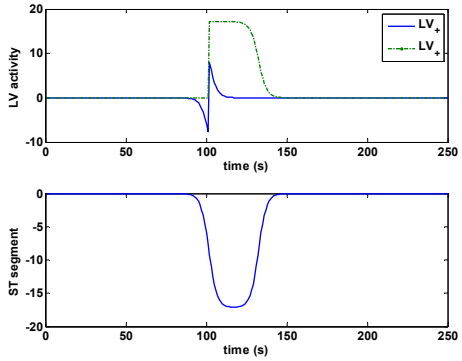

Figure 9: R wave and T wave generation.

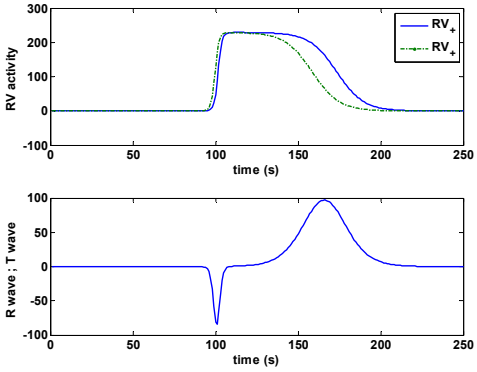

Figure 10: S wave and T wave generation.

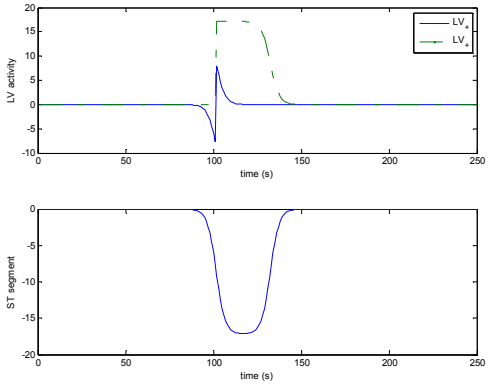

Figure 11: ST segment generation.

3.1.6 Parameter Estimation and Signal Fitting

This section discusses how to determine the parameters of the activation sequences in order to generate a real patient ECG signal. In order to achieve this task, a parameter estimation of the proposed model (1) and (2) is performed using the minimization of the least squares with the real ECG

signal. This process was performed with the help of the fmincon function, in Matlab, which finds a constrained minimum of a function for several variables. The function being minimized is given:

$$Error = \sum_{signal} \left(ECG - \hat{f}_{ECG} \right)^2, \quad (4)$$

The constraints applied to the function are that the atrial activity occurs prior to that of the ventricles. Moreover, the activation of the cell activity is constrained to occur prior to that of the deactivation. Additionally, the slopes of the activation are higher than those of the deactivation curves.

A template initial condition with known parameters for $\hat{f}_{ECG}$ is used to set the initial condition for the optimization process. Additionally, a dynamic template is generated for each beat. This choice of the template depends on the sign of the R peak. This allows more accuracy during the nonlinear optimization process. The highest cross-correlation point between the initial template the patient signal is then chosen.

Figure 12 shows the real and estimated ECG signal. It can be seen that the 'fitted' signal generated from the model matches the original patient signal. The model parameters used to generate the fitted signal are used as features in the classification process.

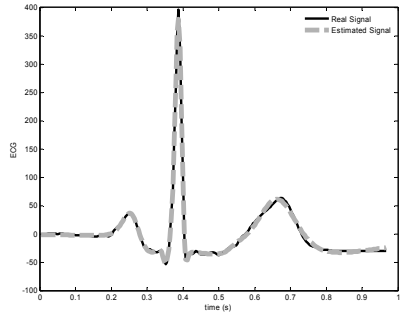

Figure 12: Estimated signal and original ECG signal.

3.2 Principle Component Analysis

Principle Component Analysis (PCA) is a linear transform where the basis functions are taken from the statistics of the signal, and can thus be adaptive. It is optimal in the sense of *energy compaction*, i.e it places as much energy as possible in as few coefficients as possible. The PCA is typically implemented using *Singular Value Decomposition*. The transform is generally not separable, and thus the full matrix multiplication must be performed:

$$X = U^T x, x = UX, \quad (5)$$

where the U is the basis for the transform. U is estimated from a number of x_i where $i \in [0 \cdots k]$:

$$\begin{aligned} U\Sigma V^T &= [x_1\, x_2 \ldots x_k] = A \\ U &= eigvec\left(AA^T \right) \end{aligned}. \quad (6)$$

3.3 C4.5 or J48 Decision Tree

Decision trees represent a supervised approach to classification. A decision tree is a simple structure where non-terminal nodes represent tests on one or more attributes and terminal nodes reflect decision outcomes. Generally, a decision tree algorithm chooses the attributes that best differentiates the output attribute values. The Weka classifier package (Eibe Frank 2007) has its own version of C4.5 known as J48. Weka's J48 is used in this work to solve the classification problem.

4 RESULTS

The HCM-PCA/C4.5 classifier is applied to the Long Term ST-Database. The proposed approach is compared to the technique proposed in (Stamkopoulos 1998). As mentioned before, the beat is detected using an automatic tool 'wqrs' provided by Physionet. The high frequency noise in the signal is removed using wavelet decomposition (Clifford 2006). The model is fitted to the model by minimizing the sum squared error using a constrained optimization process. The constraints are used to maintain the order of the heart's activation sequences. That is, the atrial activation occurs prior to that of the ventricles and the depolarization event occurs prior to the repolarization. The model parameters are used in the classification process, i.e. as features to determine whether a beat is ischemic or healthy.

A C4.5 decision tree is used in the classification process. As mentioned above, a 10 fold cross validation is performed. The classification method is applied with and without using the PCA components as features. Using the model parameters without the PCA features, the accuracy is 87.83% with sensitivity and specificity of 92.62% and 65.69%, respectively. Using the PCA features without the model parameters leads to an accuracy of 87.83% with sensitivity and specificity of 93.8% and 72.7%. However, when using the PCA features in addition to the model parameters, the accuracy increases to

91.62% with sensitivity of 94.89% and sensitivity of 75.66%. Sensitivity and specificity are defined as the accuracy of detecting the ischemic beat and the accuracy of detecting the non ischemic beat respectively. The confusion matrices for the proposed approaches are given in Table 1, Table 2, and Table 3 respectively. Confusion matrix is a visualization tool that presents the instances classified as ischemic or healthy in its columns and the actual classification in its rows.

Table 1: Confusion Matrix for HCM /C4.5 approach.

	Classified as	
	Ischemic	Healthy
Ischemic	15608	1255
Healthy	1243	2421

Table 2: Confusion Matrix for PCA/C4.5 approach.

	Classified as	
	Ischemic	Healthy
Ischemic	15877	986
Healthy	1044	2620

Table 3: Confusion Matrix for HCM-PCA/C4.5 approach.

	Classified as	
	Ischemic	Healthy
Ischemic	16035	828
Healthy	892	2772

It can be seen from Table 1 and Table 2 that the sensitivity of the proposed approach increases by 10% when using the PCA components in addition to the model parameters as features in the C4.5 decision tree classifier.

As mentioned above, the proposed approach is compared to the techniques of (Stamkopoulos 1998) as applied to the LT-ST database.

Table 4: Comparison between the proposed approach and previous methods.

Approach	Accuracy	Sensitivity	Specificity
HCM-PCA/C4.5	91.62%	94.89%	75.66%
Stamkopoulos	86.76%	91.73%	63.86%

It can be appreciated from Table 4 that the proposed HCM-PCA/C4.5 approach performs better than the previous methods by (Stamkopoulos 1998) for the LT-ST database. However, we have not been able to replicate the results of (Victor-Emil Neagoe 2003).

The importance in the proposed model, HCM, is that it can be related back to the heart's physical and electrical activity. It can be seen that the parameters of the HCM 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 ECG waves and segments, such as slope, interval duration, magnitude and segment's variation.

5 CONCLUSIONS

A HCA-PCA/C4.5 approach is presented in this work to diagnose ischemic and healthy beats. The proposed approach is applied to the LT-ST database provided by Physionet. The approach showed excellent results when diagnosing ischemic and healthy beats. The proposed modelling approach provides a method to identify the features of ECG signals and an estimate to the cellular eclectic activity useful for ischemia detection. Finally, the proposed classification approach can be extended to detect different cardiac diseases.

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APPENDIX

The cost function for the constrained optimization function is obtained by replacing (1) into (2):

$$\min_{x} \sum \left(ECG - \sum_{\substack{i=SA,AV,Bb,\\ Pf,LV,RV}} k_i \cdot g\left(t, \mathbf{a}_i, \mathbf{c}_i\right) \right)^2 , \qquad (7)$$

$$g\left(t, \mathbf{a}_i, \mathbf{c}_i\right) = d\left(t, a_{i,1}, c_{i,1}, a_{i,2}, c_{i,2}\right) - d\left(t, a_{i,3}, c_{i,3}, a_{i,4}, c_{i,4}\right) , \qquad (8)$$

$$d\left(t, a_1, c_1, a_2, c_2\right) = s\left(t, a_1, c_1\right) - s\left(t, a_2, c_2\right) , \qquad (9)$$

$$s\left(t, a, c\right) = \frac{1}{1 + e^{-a(t-c)}} , \qquad (10)$$

Subject to the constraints: $c_{(i)1,3} < c_{(i)2,4}$, $c_{(SA)1,3} < c_{(AV)1,3}$, $c_{(SA)1,3} < c_{(Rvep)1,3}$, $c_{(SA)2,4} < c_{(AV)1,3}$, $c_{(AV)2,4} < c_{(Rvep)1,3}$, $c_{(AV)2,4} < c_{(Rven)1,3}$, $c_{(AV)2,4} < c_{(Lvep)1,3}$, $c_{(AV)2,4} < c_{(Lven)1,3}$, $c_{(Rven)2,4} < c_{(Lvep)1,3}$, $c_{(Rven)2,4} < c_{(Rvep)1,3}$, $c_{(Rvep)1,3} < c_{(Lvep)1,3}$, $c_{(Lvep)2,4} < c_{(Rvep)2,4}$, $c_{(Rvep)1,3} < c_{(Lven)1,3}$, $c_{(Lven)2,4} < c_{(Rvep)2,4}$, $c_{(Lvep)1,3} < c_{(Lven)1,3}$, $c_{(Lven)2,4} < c_{(Lvep)2,4}$,
$0.05 < \left|c_{(SA)4} - c_{(SA)2}\right| < 0.12$, $0.05 < \left|c_{(SA)4} - c_{(SA)2}\right| < 0.12$
$0.05 < \left|c_{(AV)4} - c_{(AV)2}\right| < 0.10$, $0.05 < \left|c_{(Rvep)3} - c_{(Rvep)1}\right| < 0.08$,
$0.05 < \left|c_{(Rvep)4} - c_{(Rvep)2}\right| < 0.10$, $0.05 < \left|c_{(Rven)4} - c_{(Rven)2}\right| < 0.03$,
$0.05 < \left|c_{(Lvep)3} - c_{(Lvep)1}\right| < 0.03$, $0.05 < \left|c_{(Lvep)4} - c_{(Lvep)2}\right| < 0.10$,
$0.05 < \left|c_{(Lvep)3} - c_{(Lvep)4}\right| < 0.10$.