A Long Short-Term Memory Network to Classify Myocardial Infarction Using Vectorcardiographic Ventricular Depolarization and Repolarization

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Abstract

QT interval beat-to-beat variability has indicated diagnostic/prognostic abilities in myocardial infarction. Furthermore, research has suggested that vectorcardiography has superior diagnostic abilities compared to the standard electrocardiogram in myocardial infarction. This study aimed to assess the ability of vectorcardiographic ventricular depolarization and repolarization to classify myocardial infarction patients versus control subjects. 147 vectorcardiogram recordings (78 MI vs. 69 Control) were obtained from the PTB database. For each recording, 60 QRS-complex and T-wave VCG beats were extracted using the Two-Dimensional Signal Warping algorithm. An inhomogeneous three-dimensional template adaptation scheme was applied on each QRS-loop and T-loop to capture subtle morphological changes from beat-to-beat. Training was performed on a regularized three-layer long short-term memory network. The classifier produced test set classification results with an overall 89.1% accuracy, 89.1% sensitivity and 90.0% specificity. In conclusion, high classification accuracy has been achieved on a relatively small subset of the PTB database. Future work will look to improve the classification results by extending the analysis across the entire PTB database.

1. Introduction

Myocardial infarction (MI), commonly referred to as a heart attack, is a cardiac event in which the myocardium is deprived of sufficient blood supply resulting in irreversible myocardial damage. MI has been linked to a plethora of cardiac conditions including tachycardia and sudden cardiac death (SCD) [1]. Academically and clinically, MI has largely been assessed analyzing the 12-lead electrocardiogram (ECG). However, research has suggested that vectorcardiography (VCG) carries superior diagnostic abilities in MI diagnosis [2], [3]. Most significantly, VCG contains an inherent advantage over the ECG in that phasic changes are more clearly identifiable [3].

Recently, a position statement and consensus guide [4] highlighted that increased beat-to-beat QT interval variability (QTV) contains important information pertaining to sudden cardiac death cardiac diseases. In addition, elevated QTV has been observed in non-cardiac conditions such as obstructive sleep apnoea [5].

Baumert et al. suggested the importance of analyzing QT interval variability without the exclusion of the $T_{peak} - T_{end}$ interval. Moreover, the position statement recommended the use of robust template matching techniques for QTV analysis and called for advanced signal processing techniques capable of dealing with nonlinearities. To date, template adaptation techniques have produced state-of-the-art performance in ECG analysis [6], [7]. However, little attention has been placed on vectorcardiogram techniques exploring inhomogeneous template adaptation. In this work, we combine an inhomogeneous template adaptation technique to capture subtle beat-to-beat morphological changes with a long short-term memory (LSTM) classification network. Thus, this work aims to assess the diagnostic ability of ventricular depolarization and repolarization lability in MI patients using VCG.

Traditionally, machine learning research techniques have focused on utilizing various combinations of the 12-lead ECG to distinguish myocardial infarction patients from control subjects [8]. In these works various approaches have been employed for the classification task. Acharya et al. proposed the use of a convolutional neural network (CCN) on a single beat for each patient [9]. Zhou et al. proposed feeding a support vector machine polynomial for approximation coefficients of the ST segment [10]. Arief et al. describe a K-nearest neighbour classifier utilizing time domain features, namely T-wave amplitude, ST segment deviation and Q-wave amplitude. Lastly, Lui et al. propose the use of a stacked CNN-LSTM across a fixed-length period to account for beat-to-beat variability[8]. The aforementioned works have produced state-of-the-art results, however, with the exception of Lui et al. have neglected to consider long-term dependencies. Furthermore, the proposed methods have neglected to explore vectorcardiogram data.

2. Data Pre-processing

In this section, we briefly describe the inhomogeneous template adaptation signal processing technique utilized to

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filter the vectorcardiogram. The template adaptation technique is a two-fold process consisting of global adaptation via Procrustes analysis; followed by a local template adaptation utilizing a free-form deformation (FFD) parameterization and subsequent kernel ridge regression formulation (KRR). Beat-to-beat QRS-complex and T-wave delineation was performed using the Two-Dimensional Signal Warping (2DSW) algorithm [11], [12]. Subsequently, an ensemble averaged VCG QRS-loop and T-loop were generated across 60 recorded beats.

2.1. Procrustes Analysis

Procrustes analysis is a popular statistical shape registration technique employed to globally align spatial data. In this work, we utilize Procrustes analysis to globally rotate and translate the template, VCG_o ($N \times 3$ matrix), to the target, VCG_t ($N \times 3$ matrix). An independent Procrustes analysis is performed on each VCG channel to account for varying time-lags found between VCG channels of the same beat. For channel VCG_{o_c} (where $c = 1, 2, 3$) Procrustes analysis can be considered as obtaining a least squares solution to obtain an optimal rotation (R) and translation (T):

$$VCG_{g_c} = R(VCG_{o_c}) + T. \tag{1}$$

The three-channel globally adapted template,
VCG_g, is parameterized in the ensuing section using FFD.

2.2. Free-Form Deformation Parameterization

Free-from deformation is a computer graphics technique utilized to parameterize three-dimensional data to a lattice of control points bounded by a parallelepiped. In this work, for each heart beat we parameterize the globally adapted template, VCG_g, to the minimum bounding rectangular prism containing the template and the current target beat. For any sample point a of VCG_g^a, the three-dimensional sample can be parameterized to control point, P_{ijk}, by the following equation:

$$\begin{aligned} x_{ijk} = \textstyle\sum_{i=0}^{l} \binom{l}{i}(1-s)^{l-i}s^i \times \\ \Big(\textstyle\sum_{j=0}^{m} \binom{m}{j}(1-t)^{m-j}t^j \times \\ \Big(\textstyle\sum_{k=0}^{n} \binom{n}{k}(1-u)^{n-k}u^k\Big)\Big), \end{aligned} \tag{2}$$

where s, t and u denotes the embedding rectangular prism localized coordinate system. In the interest of conciseness, we do not expand on how to obtain the value of s, t and u for each three-dimensional VCG point, instead we refer the reader to the original work by Sederberg et al [13]. Parameterizing each three-dimensional sample of VCG_g to each control point of the FDD lattice yields a matrix of FFD weights, X. Mathematically, the parameterization can be expressed as:

$$VCG_g = XV, \tag{3}$$

where V denotes an 8×3 matrix of the control point spatial coordinates. In the next section we describe the underlying least squares approach of the proposed framework.

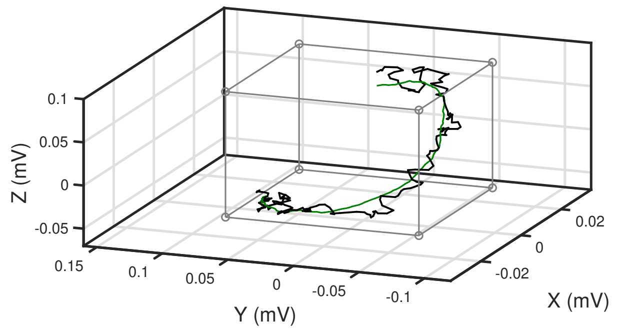

Figure 1. An FFD parameterization of a globally adapted template (green) to eight control points (grey circles).

2.3. Kernel Ridge Regression Formulation

If we wish to obtain an adapted template, where the control points of the FFD lattice are shifted to fit the VCG_g in an optimal manner to VCG_t, we can perform a linear least squares optimization. In the subsequent experiments, VCG_t refers to an extracted QRS-loop or T-loop for a subject from the PTB database. Mathematically, the optimization can be expressed as:

$$V_l = (X^T X)^{-1} X^T VCG_t. \tag{4}$$

The adapted template can then be obtained in the following manner:

$$VCG_l = XV_l. \tag{5}$$

Such a formulation is unable to capture extreme non-linearities in morphology, thus the simple linear least squares regression is extended to a KRR. In the kernelized non-parametric extension of the linear least squares solution, the described inhomogeneous template adaptation technique is defined as:

$$f^*(VCG_t, \Lambda) = K(K + c_1\Lambda)^{-1} VCG_t, \tag{6}$$

where K represents the kernelized FFD weights matrix and Λ the noise estimation square diagonal regularization matrix. The kernel function applied to the FFD weights matrix X is the Gaussian kernel:

$$k(x, x') = exp(\frac{|x - x'|^2}{2\sigma^2}), \tag{7}$$

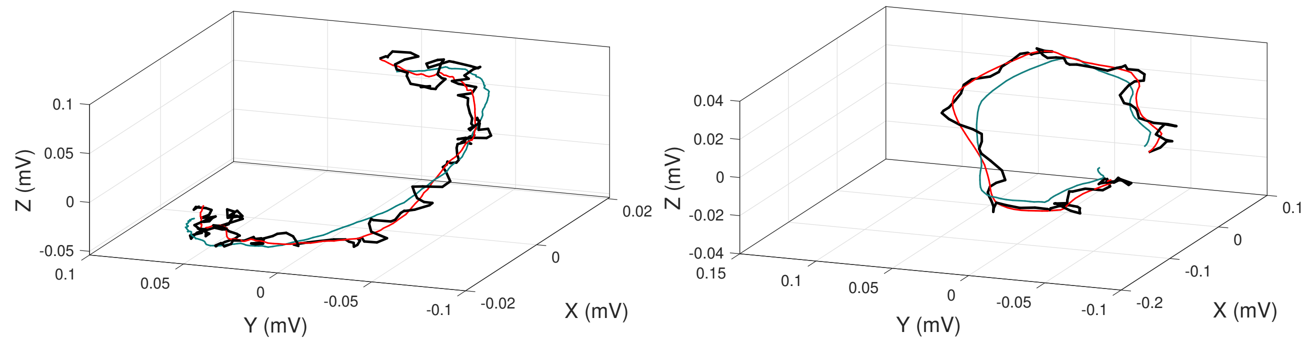

Figure 2. Examples of a VCG T-loop template before (green) and after adaptation (red) to a noisy target beat (black) in the PTB database for a MI patient (a) and control subject (b).

where σ denotes the kernel width. The kernel width determines the length of the wiggles in the Gaussian kernel function.

The noise estimation model used in this technique is based on a simple differentiator model :

$$\Lambda_a = VCG_{t_a} - VCG_{t_{a-1}}, \tag{8}$$

where Λ_a denotes the a^{th} diagonal entry in the $N \times N$ regularization matrix and VCG_{t_a} the a^{th} sample of the current VCG beat.

3. Classification

In this work, we propose the use of a deep LSTM network to distinguish between myocardial infarction patients and control subjects. LSTM networks belong to the recurrent neural network (RNN) family and were developed to overcome two key limitations of traditional RNN networks; LSTM networks address the vanishing gradient problem and the long-term dependency problem [14]. RNNs are networks with a feedback mechanism, which allow for information to persist [15]. This inherent ability to retain information across multiple time-steps makes RNNs a powerful tool in time-series classification problems. In particular, the ability of LSTM networks to capture long-term dependencies makes them an ideal candidate in cardiac time-series classification tasks analyzing beat-to-beat variability. Owing to these properties, we employ a deep LSTM network to analyze the ability of ventricular depolarization and repolarization lability to classify myocardial infarction patients.

Table 1 describes the network architecture. The input to the network consists of a 3x8280 dimension matrix. 8280 corresponds to the minimum length time-series sequence observed amongst all patients across 60 beats. Any patient with a sequence length not equal to the minimum length had their sequence shortened to the minimum length. The proposed classification architecture utilizes a three-layer deep LSTM network with with a subsequent dropout layer and fully-connected layer. The dropout layer serves as a regularization term in the network to prevent overfitting; a constant dropout rate of 5% was employed in this work. The output layer utilized the softmax activation function. The standard classification cross-entropy loss function is utilized in the proposed architecture.

Table 1. Network architecture.

Layer Number	Layer Type	Output Dimensions
0	VCG Inputs	3×8280
1	LSTM	1×2
2	LSTM	1×2
3	LSTM	1×28
4	Dropout	1×28
5	Fully-Connected	1×28
6	Outputs	1×2

3.1. Results

The performance of the proposed method was statistically evaluated utilizing the accuracy, sensitivity and specificity measures. Based on the proposed classification architecture, the system achieved a: 90% accuracy , 89% sensitivity and 90%. A 5-fold cross-validation was utilized to evaluate the network with a rounded 80/20 percent split between the model selection and independent testing data, respectively. The preliminary results obtained from this subset of the PTB database [16] suggest that the vectorcardiogram depolarization and repolarization segments contains important diagnostic information pertaining to MI diagnosis.

Table 2 illustrates the performance comparison of the proposed method to existing classification approaches in literature. The proposed method is comparable in performance to several state-of-the art algorithms. An extension of the proposed work to the entire PTB database should yield improved classification results. Furthermore, although high-results have been reported across this study and in particular across several existing studies, the analysis should be extended across an external testing database.

Table 2. Proposed technique performance comparison to existing classifiers.

Author	Sensitivity	Specificity
Lui et al.	92.4%	97.7%
Acharya et al.	95.5%	94.2%
Chang et al.	98.7%	96.6%
Arief et al.	99.6%	99.1%
Huang et al.	89.7%	84.6%
Proposed Method	89.1%	90.0%

4. Conclusion

In this paper, a diagnostic machine learning assessment of VCG ventricular depolarization and repolarization in MI patients was performed. To account for complex beat-to-beat spatio-temporal behaviour of vectorcardiogram data an inhomgeneous template adaptation technique was employed. A deep LSTM network was implemented to learn the complex beat-to-beat spatiotemporal dynamics of myocardial infarction patients and control subjects. The results suggest that the proposed analysis of VCG depolarization and repolarization may be a suitable method in MI patient diagnostics. Future analysis will look to extend the training and validation across the entire PTB database with an increased complexity level in network architecture. Classification testing will be performed across an external database to evaluate the generalization of the proposed framework.

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