Detection of Ventricular Late Potentials in High-Resolution ECG Signals by a Method Based on the Continuous Wavelet Transform and Artificial Neural Networks

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Abstract:- Ventricular Late Potentials (VLPs) are low-amplitude, high-frequency signals which appear at the end part of the QRS complex of a High-Resolution ECG (HRECG) record including three orthogonal (XYZ) leads. VLPs are clinically useful in identifying post-MI (Myocardial Infarction) patients prone to Ventricular Tachycardia (VT) and Sudden Cardiac Death (SCD). The Continuous Wavelet Transform (CWT), Principal Component Analysis (PCA), and Artificial Neural Networks (ANNs) are used to detect VLPs in this work. The terminal part of the QRS complex in the Vector Magnitude ($VM$) waveform is processed with the CWT to extract a feature vector. In this way, the resulted time-scale representation is subdivided into several regions, and the sum of the squared decomposition coefficients is computed in each region. Then, the resulted feature vector is processed by PCA to reduce its dimensionality. Finally, a supervised feedforward ANN, trained by an appropriate set of these feature vectors, is applied in the analysis of HRECG signals in order to identify VLPs. A set of different HRECG records, which includes real ECG records without VLPs and semi-simulated ECG signals with VLPs, was used to evaluate this method. The results reveal good improvements in sensitivity and specificity comparing to the conventional time-domain method, developed by Simson.

Key-Words:- Ventricular Late Potentials, High-Resolution ECG, Wavelet Transform, Neural Networks

1 Introduction
Most Sudden Cardiac Deaths (SCDs), due to cardiac diseases, are thought to be initiated by Ventricular Tachycardia (VT), one of the most serious types of cardiac arrhythmia [11]. Since the appearance of Ventricular Late Potentials (VLPs) is associated with VT, there is a clinical interest in detection of these signals as a non-invasive diagnostic marker for post-MI (Myocardial Infarction) patients prone to VT. VLPs are low-amplitude, high-frequency signals which appear at the end part of the QRS complex and arise due to the late depolarization of damaged myocardium. Because of their very low amplitudes and the noise overlay, VLPs are obscure in a standard electrocardiogram (ECG) but they can be detected by a High-Resolution ECG (HRECG) record taken using three orthogonal $XYZ$ leads with a minimum sampling frequency of 1000Hz and a resolution of 12 bits [1,9,11]. There are various techniques to improve signal-to-noise ratio (SNR) in VLP analysis. Typically several heart beats (200-300) are averaged to suppress the background noise and form the Signal Averaged ECG (SAECG).

The conventional time-domain method of VLP detection, developed by Simson [8], is based on feature extraction from the filtered SAECG [8,9,13]. Simson's method employs a high-pass filter (cutoff frequency of 25 or 40Hz) to attenuate low-frequency components of averaged $XYZ$ signals (SAECGs). To avoid the filter ringing effect in the terminal parts of QRS complex, Simson proposed a bi-directional four-pole Butterworth high-pass filter [8]. After high-pass filtering of the averaged $XYZ$ signals, these signals are combined into a Vector Magnitude ($VM$) waveform defined by

$$VM = \sqrt{X^2 + Y^2 + Z^2}$$

(1)

After estimating the onset and offset of the filtered QRS complex (the QRS complex in the $VM$ signal), three conventional time-domain features can be measured to detect VLPs [1,11,12,13]:
- $QRS_T$: Duration of the filtered QRS complex (from the onset to the offset).
- $D_{40}$: Low-amplitude signal duration (from the offset backward to the point where $VM$ reaches $40\mu V$).
- $V_{40}$: Root-mean-square value of the last $40ms$ of the filtered QRS (shadowed in Fig.1).
The criteria to define a VLP positive test are $QRS_T > 114\text{ms}, D_{40} > 38\text{ms}, \text{and } V_{40} < 20\mu\text{V}$ [11].

In Fig.1, a plot of a typical filtered QRS complex and the definition of the conventional time-domain features, introduced above, can be viewed.

In this paper, a method based on the Continuous Wavelet Transform (CWT) and Artificial Neural Networks (ANNs) is proposed to improve VLP detection. Section 2 describes the principles of the proposed method and Section 3 presents the results of applying this method to a HRECG database. Finally, The paper closes with some conclusions in Section 4.

2 Methodology

The method employed in this work, for detection of VLPs, consists of seven stages:

i. Averaging XYZ leads of the HRECG signal to improve SNR (300 heart beats).

ii. Bi-directional Butterworth Band-pass filtering of averaged XYZ signals consisting of a 4th order high-pass and a 5th order low-pass filters with cutoff frequencies of 40Hz and 250 Hz respectively.

iii. Combination of the filtered averaged signals into a $VM$ waveform using equation (1).

iv. Applying the CWT to the terminal part of the QRS complex in the $VM$ signal.

v. Feature extraction from the resulted time-scale plot.

vi. Dimensionality reduction of the resulted high-dimensional feature vector by Principal Component Analysis (PCA).

vii. Classification of the reduced dimensional feature vector by applying a Multi-Layer-Perceptron (MLP) neural network trained with an appropriate dataset.

Fig.2 shows the stages of the proposed method.

2.1 The Continuous Wavelet Transform

In the recent years, the wavelet analysis has been used widely in biomedical researches [2,5,7,14]. The wavelet transform is a linear time-scale transform which is based on decomposition of a signal using a set of basis functions. These basis functions are scaled and shifted versions of a prototype mother wavelet [4,11]. The Continuous Wavelet Transform is defined as [4,6,9,11]:

$$CWT(\tau,a) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi^*(\frac{t-\tau}{a})dt$$

(2)

where $x(t)$ is the signal of interest and $\psi(t,a)$ is the mother wavelet scaled by $a$ and shifted by $\tau$ ($\psi^*$ is conjugated version of $\psi$). The CWT produces a time-scale representation of the signal, and $CWT(\tau,a)$ is the wavelet decomposition coefficient depending on time $\tau$ and scale $a$. The scale can be considered as the inverse of the frequency [9]. The smaller scales brings about a higher resolution in time which is useful to detect VLPs as high-frequency, short-duration signals.

2.2 Feature Extraction

In this work, the CWT is applied, using the MATLAB wavelet toolbox, to the last 40ms of the QRS complex in the $VM$ signal after estimating the offset point. To improve the robustness of the method to the error in QRS offset detection, a 8ms right shift is considered for the estimated offset [13] so that the CWT is applied to 48ms interval of the $VM$ waveform, with scale range of 1-8 and the Morlet wavelet as the mother wavelet [6]. Then, The resulted time-scale representation is subdivided into 81 regions [6] (nine subdivisions on both the time and scale axes). Finally, the sum of the squared wavelet decomposition coefficients is computed in each region to form a feature vector composed of the 81 elements.

2.3 Dimensionality Reduction

Due to the high dimensionality of the resulted feature vectors, these vectors must be processed by a technique to reduce their dimensionality. In this research, Principal Component Analysis is used for...
this purpose. PCA is a statistical technique which applies an orthogonal linear transformation, defined by (3), to the original \( n \)-dimensional feature vectors.

\[
y_{d+1} = T^T x_{n+1}
\]

where \( x \) is an original feature vector \[3\].

To calculate the transformation matrix \( T \), the covariance matrix of the original training feature vectors is computed initially. Then, the eigenvalues of this matrix are calculated. These eigenvalues are sorted so that \( \lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n \). Then, the \( d \) orthogonal unit eigenvectors i.e. \( \mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_d \) associated with the first \( d \) eigenvalues \( (\lambda_1, \lambda_2, \ldots, \lambda_d) \) are set as the columns of \( T \)[3].

Before applying PCA, a normalization procedure is used to preserve discrimination of the classes (HRECG with VLP and without) in this work. According to this procedure all original feature vectors are normalized using equation (4).

\[
\hat{x}_j = (x_j - \bar{x}_{j-train} ) / \sigma_{j-train} \quad \text{for } j = 1, 2, \ldots, n
\]

where \( \mathbf{x} = (x_1, x_2, \ldots, x_n)^T \) is an original feature vector with dimension \( n \), \( \bar{x}_{j-train} \) and \( \sigma_{j-train} \) are respectively the mean value and standard deviation of the \( j \)th element of the original training feature vectors.

In this research, the dimensionality of the normalized original feature vectors is reduced to 10 by PCA using the functions of MATLAB.

### 2.4 Artificial Neural Network (ANN)

In this work, a MLP neural network with three layers is used. This feedforward artificial neural network consists of ten nodes in the input layer, a hidden layer with 15 neurons, and one neuron in the output layer. The learning algorithm for training the network is the backpropagation, and the activation function of the neurons is sigmoid \( f(x) = \frac{1}{1+e^{-x}} \).

The ANN output has a value between zero and one. The output value close to zero shows that there is no VLP in the HRECG signal, whereas this signal has VLPs if the ANN output is close to one.

### 3 Results

To evaluate the method used in this study a HRECG database consisting of two groups of signals was selected. The first group contained 50 healthy volunteers’ HRECG records acquired by a digital data acquisition system, ML785 PowerLab/8SP, with a sampling frequency of 2000Hz and a 16-bit analog-to-digital converter (ADC). The second group consisted of semi-simulated HRECG signals with VLPs. In order to simulate each of these signals, three basic simulated waveforms resembling the VLP characteristics were added to XYZ leads of a basic HRECG record, a HRECG record without VLP. VLPs are low-amplitude signals (~1-20µV) with short duration (~5-50ms) and broadband spectrum (~40-250Hz) [11]. According to these characteristics, VLPs were simulated as colored Gaussian processes resembling better the real world signals. The basic VLP waveforms were added to the end part of the QRS complex of every heart beat of the XYZ leads belonging to the basic HRECG records. The position of the VLPs was varied randomly from beat to beat with respect to the fiducial mark, QRS peak [10,11].
By choosing all of the 50 healthy HRECG signals as the basic HRECG records, fifty HRECG signals with VLPs were obtained. This HRECG database was divided into a training set, including thirty HRECG signals with VLPs and thirty without, and a test set consisting of 20 records without VLPs and 20 with.

For better training of the neural network and preserving its generalization, the training set was expanded. For this purpose, five sets containing 300 heart beats were selected from every HRECG record of training set randomly. Because of the fact that every HRECG record had at least 350 heart beats, the beat selection was done without replacement for each set. Therefore, an expanded training set consisting of 300 patterns was obtained.

The performance of the VLP detection method was measured using conventional criteria i.e. the accuracy \( ACC \), sensitivity \( SE \), and specificity \( SP \) defined by

\[
ACC = 100 \times \frac{(TP + TN)}{N}, \\
SE = 100 \times \frac{TP}{(TP + FN)}, \\
SP = 100 \times \frac{TN}{(TN + FP)}
\]

where \( N \), \( TP \), \( TN \), \( FP \), and \( FN \) are respectively the total number of patterns, the number of true positive, the number of true negative, the number of false positive, and the number of false negative [6].

Using the expanded training set and the test set, the method based on the CWT and the MLP neural network, introduced in Fig.2, was evaluated. The evaluation showed good results (\( ACC=92.5\% \), \( SE=95\% \) and \( SP=90\% \)) for the test set. Fig.3 shows classification results of the method, the ANN output, for the test set. The circles correspond to the patterns with VLPs, and the stars represent the patterns without VLPs.

To investigate the performance of the VLP detection method proposed in this work, the conventional time-domain method (Simson's method) was applied to the test set; also, a method based on applying a MLP neural network to the conventional time-domain features [4,13] was used to detect VLP. This MLP neural network resembling the other one used in the proposed method included an input layer with 3 nodes and was trained using the expanded training set. Table 1 presents the results of the proposed method in comparison with Simson's method and applying a MLP neural network to the conventional time-domain features, for the test set.

### Table 1 VLP detection results. The comparison between the proposed method, Simson's method, and applying a MLP neural network to the conventional time-domain features (for the test set).

<table>
<thead>
<tr>
<th>METHOD</th>
<th>( ACC(%) )</th>
<th>( SE(%) )</th>
<th>( SP(%) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simson's Method</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One Criterion</td>
<td>80</td>
<td>100</td>
<td>60</td>
</tr>
<tr>
<td>Two Criteria</td>
<td>75</td>
<td>80</td>
<td>70</td>
</tr>
<tr>
<td>Three Criteria</td>
<td>72.5</td>
<td>60</td>
<td>85</td>
</tr>
<tr>
<td>Applying a MLP neural network to the conventional time-domain features</td>
<td>80</td>
<td>80</td>
<td>80</td>
</tr>
<tr>
<td>The method based on the CWT and the MLP neural network</td>
<td>92.5</td>
<td>95</td>
<td>90</td>
</tr>
</tbody>
</table>

### 4 Conclusion

The purpose of this work was to investigate the capability of a method based on the continuous wavelet transform and an artificial neural network (MLP), in order to extract features and classify them...
respectively, for VLP detection in HRECGs. The results show good improvements in sensitivity and specificity comparing to Simson’s method and applying a MLP neural network to the conventional time-domain features, according to Table 1.

Another possible advantage of the proposed method may be the ability of the VLP detection in patients with bundle branch block, while Simson's method can not be used with these patients because the bundle branch block causes the QRS duration to be extended and consequently increases QRST.

Simson's method is very sensitive to QRS offset, and even a few errors in estimating of this point can result in wrong diagnostic. However the method used in this study is robust to the error in QRS offset detection.

The results represented in Table 1 shows that the CWT based features, used in this study, are more capable than the conventional time-domain features to detect VLPs using MLP neural networks.

According to the above advantages, the proposed method may be an appropriate alternative method for the clinical detection of VLP, if it is evaluated completely.

Due to the lack of real HRECGs with VLPs in this research, the proposed method must be applied to a larger HRECG database consisting of real signals with and without VLPs to complete the evaluation.

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References: