Myocardial Infarction Prediction based on Natural-ordered complex Hadamard transform

Thripurna Thatipelli\textsuperscript{1} \& Padmavathi Kora\textsuperscript{2}

\textsuperscript{1,2} Department of E.C.E, Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, Andhra Pradesh

Abstract—Electrocardiogram (ECG), a non-invasive diagnostic technique, used for detecting cardiac arrhythmia has gained attention in recent years in medical sciences, industry dealing with Bio-medical instrumentation and research, demanding an advancement in its ability to distinguish different cardiac arrhythmia. Studies conducted in this research work on recent feature extraction methods yielded a lot of features. A large number of these features might be insignificant containing some redundant and non-discriminative features that introduce computational burden and loss of performance. A novel technique to classify the ECGs of normal and subjects at risk of MI using nonlinear technique has been presented. We have predicted MI by analyzing four minutes of ECG signals by using NCHT coefficients. This paper presents Natural-ordered complex Hadamard transform for extracting relevant features from the ECG signal. The sparse matrix factorization method is used for developing fast and efficient NCHT algorithm and its computational burden is examined as compared to that of the HT. The applications of the NCHT in the ECG based MI detection is also discussed. In this work, we have achieved good classification accuracy for prediction of MI. The proposed method is able to detect a person at risk of MI earlier than other methods in the literature.

Keywords—MI, ECG, NCHT, Neural Network Classifier.

I. Introduction

One of the most common form of cardiac abnormality is Myocardial Infarction (heart attack) arises when the artery connecting the heart is blocked and there is no sufficient blood or oxygen, which makes the cells present in that region of the heart to die. The MI and normal beats are shown in Figures 1 and 2.

This paper aims to process and classify an ECG signal as healthy subject or subject diagnosed with Myocardial Infarction (MI) using Artificial Neural Networks (ANN), K-Nearest Neighbour (KNN) and SVM (Support Vector Machine) Classifiers. Various algorithms for the feature extraction of ECG signal are like Haar transform (Hat)\textsuperscript{[1]}, the Karhunen-Loeve transform (KLT) \textsuperscript{[2]}, Wavelet Trans-form (WT) and the Discrete Cosine Transform (DCT) \textsuperscript{[3]}, The Fast Fourier Transform (FFT) performs signal transformation from time to frequency domain for some of the applications \textsuperscript{[5]}. The DCT is widely held for its optimum energy compaction property because the division of the average energy of the signal is grouped into a comparatively a small number of constituents of the DCT-coefficients. The DWT \textsuperscript{[6]} is familiar for its analysis for image and signal processing in multi-resolutional pattern. In the real time applications advanced fast algorithm like Hadamard Transform...
values ($\pm 1, \pm j$). It has been found in many useful applications such as signal representation and classification, spectral analysis and synthesis of voice signals, etc. But due to its limitation to the real-valued data sequences, complex version of BIFORE transform called complex BIFORE transform (CBT) which can process the complex-valued input functions was developed. This transform is based on four-valued complex Walsh functions, which consists of the elements ($\pm 1, \pm j$). Basically, the CBT is defined based on a recursive formula which assigns one class of complex Hadamard matrices involving the diagonalization of higher order matrices and multiple Kronecker products.

2. Pre-Processing

MI database and traditional Normal Sinus Rhythm (NSR) information were acquired from the MI and NSR database of MIT-BIH database. From the MIT-BIH database, MI data files of 26 people and Normal Sinus Rhythm (NSR) files of 18 people are used to detect MI. All the MIT-BIH database was not sampled at 360 samples per second. The sampling rate of a normal signal is 128 Hz and MI signal is 250 Hz. The obtained MI signals of 4 minutes length measure any signal divided into four one minute intervals. The signals obtained are then subjected NCHT for feature extraction.

3. Feature extraction

Feature extraction is the important step in the detection of heart arrhythmia. Each ECG beat consists of large number of features and many of them might be insignificant.

In this paper NCHT extracts the features of each cardiac beat.

4. Feature extraction

In this section, we shall introduce another ordered version of complex Hadamard transform called natural-ordered complex Hadamard transform (NCHT). Its order corresponds to that of the WHT matrices (i.e., natural or Hadamard order). It can be seen that NCHT is a complex counterpart of the WHT. Generally, NCHT is a discrete orthogonal transform whose elements are confined to four complex integer values ($\pm 1, \pm j$), and its row vectors are orthogonal to each other in the complex domain.

The construction of the NCHT is based on the WHT and the direct block matrix operation (which is to be defined later in this subsection). Before going directly into the generation of the NCHT, we first describe the construction of the WHT. The WHT matrix $W_N$ is a square and symmetric matrix which is defined as
\[
W_n = \begin{bmatrix}
W_{N/2} & W_{N/2} \\
W_{N/2} & -W_{N/2}
\end{bmatrix}
\]

where \( W_1 = 1 \) and \( N = 2^n \). The NCHT matrix is also constructed using a similar way of generating a WHT matrix but the multiplication via the S matrices are introduced in the lower half of the matrix. Let \( H_n \) be any NCHT matrix of size \( N \times N \). Then, it is a square matrix defined by

\[
H_N = \begin{bmatrix}
H_{N/2} & H_{N/2} \\
H_{N/2}S_{N/2} & -H_{N/2}S_{N/2}
\end{bmatrix}
\]

Where \( N = 2^n \)

\[
S_{2^n-1} = \begin{bmatrix}
I_{2^n-2} & 0 \\
0 & jI_{2^n-2}
\end{bmatrix}
\]

and \( I_{2^n-2} \) is the identity matrix of order \( 2^{n-2} \times 2^{n-2} \). In this way, an \( N \times N \) NCHT matrix can be constructed using the NCHT matrices of size \( (N/2) \times (N/2) \), and the smallest dimension of the NCHT matrix is \( 4 \times 4 \) which is expressed as

\[
H_n = \begin{bmatrix}
1 & 1 & 1 & 1 \\
1 & -1 & 1 & -1 \\
1 & 1 & -1 & -1 \\
1 & -1 & -1 & 1
\end{bmatrix}
\]

5. Results and Discussion

For this work, from the 24 hours of MI patients ECG recordings, only the ECG signals four minutes before the MI occurrence (onset) are used. The ECG signals obtained are then subjected to wavelet based denoising using daubechies 6 (db6) mother wavelet. From the 24 hours ECG recordings, MI signals of 10 minutes are extracted and only the four minutes duration MI is used for further analysis. The obtained MI signals of four minutes duration are further divided into four one minute intervals. The algorithm has been implemented in Matlab 7.12.0. In this paper NCHT is used as the feature extraction technique. The NCHT gives best features for the classification. The performance of NCHT is compared with classical HT, NCHT techniques. The NCHT features are classified using LM NN as in the Table I. For measuring accuracy two parameters Sensitivity (Sen) and Specificity (Spe) are calculated using the following equations.

\[
\text{Sen} = \frac{\text{Correctly classified MI beats}}{\text{Total MI beats}} \times 100 \quad ----(2)
\]

\[
\text{Spe} = \frac{\text{Correctly classified normal beats}}{\text{Total normal beats}} \times 100 \quad ----(1)
\]

\[
\text{Accuracy} = \frac{\text{Correctly classified beats}}{\text{Total beats}} \times 100 \quad ----(3)
\]

The classification accuracy of KNN classifier with NCHT optimized features is 80.9% for the detection of MI. The classification accuracy of SVM classifier with

| TABLE I |
| --- | --- | --- |
| Classifier | Sen | Spe |
| NCHT+KNN | 91.2% | 89.2% |
| NCHT+SVM | 89.34% | 89.2% |
| NCHT+LMNN | 98.97% | 98.7% |

NCHT optimized features is 89.2% for the detection of MI. Results show that optimized NCHT features in combination with LMNN classifier shows better results than KNN and SVM classifiers for the detection of MI. The classification accuracy of LMNN classifier with NCHT features is 98.3% for the detection of MI. Voss et al. [12] used frequency and time domain features of 26 cardiac patients after MI using non-linear methods and renormalized entropy. They observed 96% classification using the combination of all features. Shen et al. [11] developed a personal cardiac model for MI detection from ECGs. They observed classification accuracy of 87.5% using wavelets for the detection of MI. Elias et al. [14] in their study developed a novel approach to predict MI one, two, three and four minutes before its onset using nonlinear and TF analysis of heart rate variability signals. The algorithm extracted time-frequency features of average energy and nonlinear features of Poincare plot and non-linear short-term fractal scaling exponent from heart rate variability signal and used MLP and KNN classifiers to predict the patients with MI. Manis et al. [13] designed a machine learning technique to predict high and low risk MI signals after arrhythmia in heart patients using HRV analysis. They obtained a classification accuracy of 87.5% by using SVM, and 85% by using Random Forest classifiers for the detection of MI[15]. The proposed method shows the highest classification accuracy for the detection of MI. The NCHT have been employed intelligently to select the most relevant features that could increase the classification accuracy while ignoring noisy and redundant features.
6. Conclusion

ECG is used to access the electrical activity of a human heart. In this study our aim is to automate the above procedure so that it leads to correct diagnosis. Early diagnosis and treatment is of great importance because immediate treatment can save the life of the patient. The proposed fast NCHT method is used to extract the features from each ECG beat then these features are compared to HT, NCHT algorithm. The classification accuracy using NCHT with LMNN classifier was 98.3% for the detection of MI. The experimental results have shown that the proposed NCHT method can extract more relevant features than the other methods proposed in the literature with highest classification accuracy for the detection of MI.

7. References


TABLE II

Comparative study for detection of MI

<table>
<thead>
<tr>
<th>Studies</th>
<th>Approach</th>
<th>Sen (%)</th>
<th>Spe (%)</th>
<th>Acc (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shen et al. (2007) [11]</td>
<td>Wavelet analysis (db2) and HRV analysis using FFT</td>
<td>75</td>
<td>—</td>
<td>87.5</td>
</tr>
<tr>
<td>Voss et al. (1996) [12]</td>
<td>Linear and Nonlinear dynamic methods</td>
<td>—</td>
<td>—</td>
<td>96</td>
</tr>
<tr>
<td>Manis et al. (2013) [13]</td>
<td>Linear and Nonlinear features</td>
<td>—</td>
<td>—</td>
<td>87.5</td>
</tr>
<tr>
<td>Elias et al. (2014) [14]</td>
<td>Linear time domain, frequency domain features</td>
<td>97.64</td>
<td>98.27</td>
<td>97.03</td>
</tr>
<tr>
<td>Proposed approach</td>
<td>NCHT</td>
<td>96.97</td>
<td>98.2</td>
<td>98.3</td>
</tr>
</tbody>
</table>

