A NARX Model to Predict Myocardial Ischemic Beats from ECG Using Features Extracted by ICA and WPD

To cite this article: H. S. Niranjana Murthy 2019 J. Phys.: Conf. Ser. 1362 012100

View the article online for updates and enhancements.
A NARX Model to Predict Myocardial Ischemic Beats from ECG Using Features Extracted by ICA and WPD

H.S. Niranjana Murthy

Abstract—This paper presents a methodology for predicting Myocardial Ischemic Beats from ECG signal using a Nonlinear Autoregressive Neural Network with Exogenous inputs (NARX) model. This technique utilizes the features extracted by integrating independent component analysis (ICA) and Wavelet packet decomposition (WPD) on ECG for detecting Myocardial Ischemic beats. At first, the denoised ECG beat segments are projected on the bases to create the independent component (IC) vectors. Further, these IC vectors are disintegrated by WPD. The feature set for distinguishing ischemic beats is extracted by calculating entropy, mean and standard deviation from wavelet coefficients. These features are input to NARX model for uncovering ischemic beats from normal beats. Several architectures of NARX models were tested for predicting myocardial ischemic beats. The efficacy of NARX architectures are assessed by comparing MSE and correlation coefficient. The NARX model with 2 hidden neurons and 2 delay lines provided the best results with a MSE of 0.0002 and correlation coefficient 0.99, which implies that the NARX neural network has huge potential in the prognosis of Myocardial Ischemic Beats.

1. INTRODUCTION

Myocardial Ischemic coronary illness is the main source of death around the world. One of the risk components of cardiovascular issue is atherosclerosis and this abnormality can be forecasted by recognizing ischemia. Myocardial ischemia is a cardiovascular anomaly which impacts the heart and coronary vessels. This circumstance blocks the oxygenated blood to the strong structure of heart. Myocardial ischemia hints at the T wave alternance and ST-section changes in ECG [1]. A brief timeframe of cardiovascular ischemia may prompt reversible impacts bringing about recovery of heart muscles. The longtime enduring ischemia causes expire of heart tissue prompting myocardial dead tissue. In the last decade, there has been an extreme exertion in creating algorithms for finding myocardial ischemia utilizing ICA. The use of ICA to ECG is moderately novel and quickly developing territory of research work. A system using ICA is most helpful in revealing the covered clinically valuable data in ECG for sorting heart beats for arrhythmia location [2]. The noteworthy consequences of joining ICA and neural system has turned out to be a potential strategy for the computer aided prognosis of cardiac ailments with ECG [3]. Another procedure dependent on combination of ICA and neural system has indicated promising outcomes in extricating fundamental segments ECG.

Feature extraction is the fundamental stage in classification and it is not constrained to registering parameters yet helps in catching hidden property of ECG [4]. Inexhaustible writing is accessible on techniques of mining highlights from ECG, for example, morphological highlights, relationship measurement and wavelet transform. Transient features such as RR-interim and heart beat interim mined from time area signals have better resolution in time space as it were. For better resolution in time and recurrence areas, the statistical features were extracted by applying Wavelet Transform (WT) on the ECG signal [5]. The WT gives sufficient resolution at low frequencies yet debases at high frequencies. Then again, the WPD is created which have the capacity to accomplish sufficient resolution at the two
frequencies. In this manner, for the exact location of signal variations from ECG signal which prompts to detection of ischemic beats with improved precision of recognition, the proposed work includes the advancement of a mechanized analysis framework by coordinating ICA with WPD.

In this work, NARX recurrent neural network (RNN) [6] is proposed for foreseeing myocardial ischemic beats from ECG utilizing ICA and WPD. This is a powerful class of models which has been shown that they are appropriate for demonstrating nonlinear frameworks and uncommon time series. Some of essential characteristics of NARX networks with gradient-descending learning algorithm are: (1) learning is more powerful in NARX systems than in other neural network and (2) these systems converge speedier and has generalization capacity better than various frameworks [7]. The simulated outcome demonstrated that NARX systems are improvised at discovering long time-dependences than ordinary RNN. One of the issues related in gradient based training algorithm for learning long-term dependencies is the vanishing gradient [8]. The installed memory in NARX neural system can lessen the impact of vanishing gradient and furthermore help to accelerate proliferation of gradient information. There are different strategies for bringing memory and time-based data into NARX model. These incorporate putting time delays into the neurons, making a spatial portrayal of temporal patterns or utilizing recurrent connections and so forth.

This paper is composed with the end goal of delineating ischemic beats, the methodology included which contains preprocessing of ECG, ICA & WPD, highlight feature extraction strategy and NARX neural network. Further, performance assessment and investigating outcomes for forecast of myocardial ischemic beats are examined in ensuing area.

2. METHODOLOGY

A. Preprocessing of ECG Signal

The proposed work adopts soft wavelet thresholding method for noise removal from ECG [9]. In the denoising process, ‘rigrsure’ thresholding rule is chosen for optimal performance and wavelet function used is ‘coif2’. Next, the ECG beats are fragmented between R-R intervals which contain clinically valuable information for detecting ischemic beats. After fragmentation, RT segment is extracted which is projected on to the ICA bases to constitute feature vectors. In the proposed work, ECG signal records are obtained from European ST-T datasets whose sampling frequency is 250 Hz. The annotations of ECG records obtained provide the information of ischemic and normal beats.

B. ICA and WPD

Independent Component Analysis is a technique that breaks down the multivariate data into a linear sum of statistically independent components. The ICA uses high-order statistics and second-order statistics to lessen high-order dependency. It can be applied on ECG in feature extraction stage and its application still retains diagnostic important information in ECG signal.

The independent components (ICs) are obtained by increasing the non-gaussianity of diverse vectors in the subspace. This work utilizes a fast ICA algorithm to obtain the ICs [10]. FastICA algorithm detects the projections that maximize the non-gaussianity of components by computing their kurtosis.

The current work utilizes fast ICA algorithm in an atypical way. As an alternative of doing blind signal separation, it is used to detect the myocardial ischemic beats by determining the ICs of RT segments that are independent to one another statistically. Thereby the selected significant ICs forms the feature vectors which retain the time domain and morphological features which can be used as input to classifier after passing through wavelet packet decomposition stage.

In Wavelet Packet Decomposition, signal is passed through a sequence of low and high-pass filters concurrently [11]. This leads to more accurate signal analysis than DWT. In WPD, each detail coefficient
is also broken down into detailed and approximate coefficient vector similar to splitting of approximation vector. This results in accurate extraction of clinically useful features from signal.

Fig.1 depicts the wavelet-packet decomposition of ECG signal up to four levels. The top level is the time domain representation of the RT segment of ECG beat. The lower level indicates the frequency domain depiction of the signal, which breaks down RT segment into detail and approximation coefficients. With the ECG beat segment disintegration done from top down approach, time domain resolution diminishes, whereas the frequency resolution improves.

![Decomposition of ECG signal using wavelet packet transform](image)

Fig. 1: Decomposition of ECG signal using wavelet packet transform

**C. Feature Extraction**

In this study, the RT segment of each ECG beat is classified as ischemic or normal. The extracted samples in RT segment interval has all the information regarding morphological deviations of T wave and ST-segment, which helps in distinguishing ischemic beats.

In the proposed work for ECG beat classification, the ECG beat samples in RT segment interval is extracted at first. Secondly, RT segments are projected on the bases to create the independent component vectors and then broken down by WPD. The ICA feature vector is normalized before performing wavelet packet decomposition. Four level Wavelet packet decomposition as discussed in previous sub-section is used to obtain features from ECG.

After WPD, for distinguishing between normal and ischemic beats, features such as entropy, standard deviation and mean are computed from wavelet coefficients of each sub band as:

\[
M_i = \frac{1}{N_i} \sum_{j=1}^{N_i} |w_i(k) |
\]  \hspace{2cm} (1)

\[
Std_i = \sqrt{\frac{1}{N_i} \sum_{j=1}^{N_i} (|w_i(k)| - \bar{|w_i|})^2}
\]  \hspace{2cm} (2)
\[ E_n = -\sum_{l=0}^{i} h_i(l) \times \log_2(h_i(l)) \]  \hspace{1cm} (3)

Where \( k \) denotes the number of coefficients and \( i \) represents the number of sub-bands of wavelet packet transform, \( h_i \) is the histogram of coefficients at \( w_i \) sub-band, and \( L \) is the number of levels of histogram.

At the end of this stage, a set of 9 vectors is resulted for each ECG beat which are fed as inputs for classifiers.

D. NARX Neural Network Model

The NARX neural network model uses exogenous inputs in its computations. The NARX model will use a feedforward network with memory (tapped delay line) and a delayed connection from the output of second layer to input as shown in fig.2. The input to NARX neural network is a time window (\( d_u \) lags of input sequence elements) which provide limited view on the part of time series. It can be seen as a basic method for changing the transient measurement into another spatial measurement [12]. In the current work, the NARX model is preferred for predicting myocardial ischemic beats, since it uses limited feedback without any computational loss.

![Fig. 2: General Structure of NARX Model](image)

The NARX model is mathematically modelled by the characteristic equation

\[ y(k + 1) = F[u(k), u(k - 1), u(k - 2), \ldots, y(k), y(k - 1), y(k - 2), \ldots] + b \] \hspace{1cm} (4)

In the above equation, the \( y(k+1) \) corresponds to the output of NARX model. The \( u(k), u(k-1), \ldots \) denote the past observations of input time series. The function \( F \) corresponds to the mapping done by means of multilayer perceptron. The \( y(k), y(k-1), \ldots \) denote the past outputs, which are feedback to input for computing output.
3. RESULTS AND DISCUSSIONS

Fig. 3 denotes the denoising and segmentation of ECG signal e0603. Table 1 depicts the features obtained from wavelet coefficients of selected frequency bands decomposed by ICA projected beats using WPD on an exemplary ECG record e0603 as discussed in previous section. From the table, it is seen that the extracted features of the two types of beats are distinctive. Thus, these features can provide clinically significant criteria for detecting ischemic beats.

| TABLE 1: EXTRACTED FEATURES FROM WAVELET COEFFICIENTS OF ECG BEATS FOR AN EXEMPLARY RECORD E0603 |
|---------------------------------------------|
| **ECG Beat types** | **Beat No.** | **Sub band** |
|                |            | i = 1 | i = 2 | i = 3 |
| Normal Beats   | **Mean**   | 1.5933 | 0.4121 | 0.0255 |
|                | **Standard Deviation** | 1.4826 | 0.1891 | 0.0362 |
|                | **Entropy** | 2.8138 | 3.7345 | 2.9110 |
| Myocardial Ischemic Beats | **Mean** | 0.4746 | 0.1507 | 0.1255 |
|                | **Standard Deviation** | 0.1607 | 0.2058 | 0.2545 |
|                | **Entropy** | 3.9698 | 3.4992 | 3.1463 |

Fig. 3: Denoising and segmentation of ECG record e0603.

In this work, experiments are conducted with several architectures of NARX model with different numbers of hidden layers and tapped delay lines. The NARX models are trained with Levenberg-Marquardt backpropagation algorithm with learning rate equal to 0.001. The performance of NARX models are evaluated by varying the number of hidden layer neurons from 2 to 15 and the number of tapped delay lines from 1 to 4. The NARX model is cross-validated with ECG record containing 400 beats. The data
is divided into 70%, 15% and 15% for training, validation and testing respectively.

Fig. 4 shows the performance plot of NARX model with 2 hidden neurons and 2 tapped delay line. From the plot, it is evidential that the network has shown best performance with least value of MSE for test set.

![Performance Plot](image)

**Fig. 4:** Performance Plot for NARX model with 2 hidden neurons and 2 delay lines

Table 2 illustrates the MSE and correlation coefficient (R) of several NARX architectures. From table 2, it is evidential that the NARX model with 2 hidden layer neurons and 2 tapped delay lines has outperformed with lowest MSE of 0.0002 and highest R of 0.99.

| No of Delay Lines | No of Nodes | MSE | R  | MSE | R  | MSE | R  | MSE | R  |
|-------------------|-------------|-----|----|-----|----|-----|----|-----|----|
| 1                 | 2           | 0.098 | 0.7 | 0.0002 | 0.99 | 0.034 | 0.84 | 0.0018 | 0.99 |
|                   | 3           | 0.007 | 0.96 | 0.003 | 0.98 | 0.051 | 0.76 | 0.062 | 0.77 |
|                   | 4           | 0.018 | 0.87 | 0.001 | 0.99 | 0.009 | 0.94 | 0.006 | 0.99 |
|                   | 5           | 0.068 | 0.62 | 0.035 | 0.69 | 0.002 | 0.98 | 0.001 | 0.99 |
|                   | 6           | 0.04  | 0.84 | 0.012 | 0.93 | 0.001 | 0.99 | 0.005 | 0.94 |
|                   | 7           | 0.0007 | 0 | 0.003 | 0.98 | 0.009 | 0.95 | 0.047 | 0.53 |
|                   | 8           | 0.003 | 0.98 | 0.033 | 0.84 | 0.003 | 0.98 | 0.063 | 0.78 |

**TABLE 2: PERFORMANCE OF NARX NEURAL NETWORK MODEL**
4. CONCLUSION

This paper exhibited a NARX neural network model for detecting myocardial ischemic beats by integrating ICA and WPD. The feature vector is generated by wavelet coefficients of sub-bands formed by WPD on ICA projected ECG beats. Various NARX architectures with different numbers of hidden neurons and tapped delay lines are considered for identifying ischemic beats. The results clearly confirmed that the NARX model with 2 hidden neurons and 2 tapped delay lines has outperformed with lowest value of MSE and highest value of R. Hence, the NARX model can be used for prognosis of myocardial ischemic beat with high accuracy.

5. REFERENCES

[1] C. Papaloukas, A. Likas, L. Michalis and D. Fotiadis, “Automated Methods for Ischemia Detection in Long Duration ECGs”, CRR Journal, 24(6), pp. 313-20, 2003.

[2] S.N. Yu and K.T. Chou, “Categorizing Heartbeats by ICA and SVM”, ICIADA-2008, 1, pp. 599-602, 2008.

[3] K.T. Chou and Sung-Nien Yu, “Integration of ICA and NN for ECG Beat Classification”, Expert Syst Appl, vol.34, pp.2841-49, 2008.

[4] Y. Kutlu and D. Kuntalp, “Feature Extraction for ECG Heart Beats using HOS of WPD Coefficients”, CMPB, vol.105(3), pp. 257-267, 2012.

[5] T. Mar, J.P. Martinez, M. Uamedo, S. Zaunseder, and R. Poll, “Optimisation of ECG Classification by Means of Feature Selection”, IEEE TBME, vol. 58(8), pp.2168-77, 2011.

[6] Simon Haykin, Neural Networks and Learning Machines, Third Edition, Pearson Education, 2016.

[7] Lin Tsungnan, Peter Tino, C. Lee Giles, Bill G. Horne, “Learning Long-term dependencies in NARX RNN”, IEEE Trans. on NN, Vol.7, No.6, 1996, pp. 1329-1351.

[8] Lin Tsungnan, Bill G. Horne, C. Lee Giles, S.Y. Kung, “A Delay Damage Model Selection Algorithm for NARX NN” IEEE Tran. on SP, vol. 45, No.11, 1997, pp. 2719-2730.

[9] Murthy H.S.N and M. Meenakshi, “Optimum Choice of Wavelet Function and Thresholding Rule for ECG Signal Denoising”, IC-SSS, IEEE publisher, vol.1, pp. 1-5, 2015.

[10] Hyvarinen A, “Fast and Robust Fixed Point Algorithms for Independent Component Analysis”, IEEE Trans NN, vol.10, pp.557-564, 1999.
[11] T.Liu, M.Zang, Y.Si, L.Lang and D.Wen, “Dictionary learning for VQ feature extraction in ECG beats classification”, Expert Syst Appl, Vol.53, pp. 129-37, 2016.

[12] Diaconescu Eugen, “The Use of NARX Neural Networks to Predict Chaotic Time Series”, WSEAS Transactions on Computer Research, Vol. 3(3), pp. 182-191, 2008.

[13] NHK K. ISMAIL*, ”Estimation Of Reliability Of D Flip-Flops Using Mc Analysis”, Journal of VLSI Circuits And Systems 1 (01), 10-12, 2019.

[14] Sulyukova,”Analysis of Low power and reliable XOR-XNOR circuit for high Speed Applications”, Journal of VLSI Circuits And Systems 1 (01), 23-26, 2019.