Arrhythmia Classification and Prediction : Electrocardiograms patterns analysis using Artificial Neural Network and non-linear regression

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3 authors:

Abdou Abdoul-Dalibou
Université de Thiès

Ndeye Fatou Ngom
Ecole Polytechnique de Thiès, thiès, Senegal

Oumar Niang
Ecole Polytechnique de Thiès

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Abdoul Dalibou ABDOU ** — Ndeye Fatou NGOM* — Oumar NIANG *

* Laboratoire Traitement de l'Information et Systémes Intelligents (LTISI)
Département de Génie Informatique et télécommunication (GIT)
Ecole Polytechnique de Thies (EPT)
Thiès, Sénégal
fngom@ept.sn,oniang@ept.sn
** École Doctorale Développement Durable et Société (ED 2DS)
Université de Thiès
Thiès, Sénégal
abdould.abdou@univ-thies.sn

RÉSUMÉ. Les techniques d'intelligence artificielle sont trés performantes pour l'identification et l'extraction d'informations pertinentes à partir de données biomédicales. Cependant, pour les maladies du coeur, il existe toujours des difficultés à trouver des solutions basées sur l'apprentissage automatique efficaces pour l'aide à la prise de décision lors de diagnostic d'arythmies. Dans ce papier, nous proposons un système automatisé de classification et de prédiction basé sur un réseau neuronal artificiel pour l'arythmie cardiaque à l'aide d'électrocardiogrammes (ECG). Une analyse adaptative basée sur la décomposition modale empirique (EMD) est d'abord effectuée pour le débruitage du signal et la détection des principaux attributs d'un Ecg. Ces attributs sont ensuite utilisés en entrée du réseau neuronal afin de classer l'arythmie. les résultats de la classification sont combinés avec le rythme cardiaque pour effectuer une prédiction d'arrythmies bas'ee sur la régression non linéaire. Les modèles sont testés avec la base de données MIT BIH Arrhythmia et les résultats comparés à d'autres études. Une amélioration de 5.56% et 6.67% a été noté respectivement pour la classification et la prédiction.

ABSTRACT. Artificial intelligence techniques have been proven useful for the identification and the extraction of relevant information from biomedical data. However for hearth diseases, there still have difficulties in delivering efficient machine learning based on methods to be applied in arrhythmia diagnostic decision supports. In this paper we propose an automatic artificial neural network (ANN) based on classification and prediction system for cardiac arrhythmia using heartbeat recordings. An adaptive analysis based on an Empirical Mode Decomposition (EMD) is first carried out to perform signal denoising and the detection of main Ecg patterns. The ECG pattern are then used as input for an ANN to classify arrhythmia. The classification results are combined with hearth rhythms to perform non-linear regression based prediction of arrhythmia. The models are prepared and tested with the MIT-BIH database. An improvement of 5.56% and 6.67% was noted respectively for classification and prediction.

MOTS-CLÉS : Électrocardiogramme, Décomposition modole empirique, Réseau de neurones, Classification, Modèle prédictif, Fréquence cardiaque, Arythmie

KEYWORDS : Electrocardiogram, Empirical Mode Decomposition, Neural Network, Classification, Predictive model, Hearth rate, Arrhythmia

1. Introduction

Hearth disease is one of the leading cause of death around the world. Therefore, the understanding of hearth anomalies have become a main research topics in the field of cardiac care. An anomaly is an abnormality that occurs when the behavior of the system is unusual and significantly different from previous normal behavior [1]. Today with the advances of computer sciences for signal interpretation, electrocardiogram (ecg) analysis one of the most promising cardiac diagnostic approach that can provides valuable information about heart condition. The main steps involved in ecg analysis are abnormalities detection, classification and prediction. Anomalies detection methods are based on adaptive sampling [2] and ECG feature extraction using adaptive methods such as wavelet transform [3] or empirical mode decomposition [4]. Classification is usually performed with K nearest neighbor [5], super vector machine [6] and Neural Network models [4, 7, 8]. Unlike detection and classification methods approaches, predictive models gives indicators for possible abnormalities before the symptoms occur from historical data and an intelligent system. Few studies aimed arrhythmia prediction and most of them are based on linear model[9, 10]. In this paper, artificial neural network and empirical mode decomposition are first used for hearth anomalies detection and classification. Then the ANN outputs is used as input of non linear regression model as input for arrhythmia arrhythmia scheme. The main contributions are the ECGs morphological and frequency properties taken as input during the classification, and the predictive model based on non linear hearth rate frequency analysis. The proposed approach is illustrated using MIT-BIH database, compared to other studies and discussed.
The body of the paper is organized as follows. Section 2 presents the architecture of our methodology, the basics of the empirical mode decomposition and the neural network classifier. Section 3 describes the filter parameter extraction. Section 4 presents the classification method. Section 5 describes the predictive model. Section 6 shows and discusses about the results obtained with our methodology. Section 7 draws conclusions and perspectives of work.

2. Model Presentation

The step processing for the proposed approach is presented in the Figure 1. The inputs of the system are ECGs. For the MIT-BIH database, each ECG includes three components : time of samples, MLII signal and V5 one. For the classification, we first extract the V5 signal, then denoise the signal through filtering and compute input parameters (Negative form, maximum amplitude, minimum amplitude, maximum width maximum, minimum width, hearth rate and hearthbeat) for the neural network classifier. The outputs of the anomalies detector are then used during the arrhythmia classification and prediction steps. For this purpose, we first compute the 10 previous hearth rate, then we estimate the hearth rate at t (prediction horizon) and we predict the existence or not of arrhythmia.

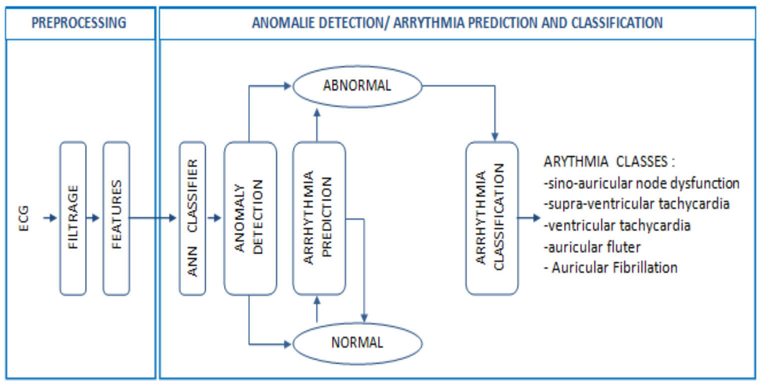

Figure 1. *Chart Flow of the proposed classification and predictive approach.*

2.1. Preprocessing

2.1.1. Empirical mode decomposition

In this study, the ecgs denoising process is done using empirical mode decomposition (EMD). EMD decomposes iteratively a complex signal s(n) into elementary components AM-FM Types, called Intrinsic Mode Functions (IMFs) [11].

$$s\left(n\right) = r_k\left(n\right) + \sum_{k=1}^{K} imf_k\left(n\right) \qquad [1]$$

Where imf_k is the k^{th} mode or IMF of the signal and r_k is the residual trend. The sifting procedure generates a finite number of IMFs. The underlying principle of the EMD is to identify locally in the signal, the fastest oscillations defined as the waveform interpolating the local maxima and minima. To do this, these last points are interpolated with a cubic spline to produce the upper and lower envelopes. The average envelope is subtracted from the initial signal and the same interpolation scheme is reiterated.

2.1.2. Filtering

Usually a real ECG signal faces muscular noise, motion artifacts, and baseline drifts changes. Butterworth filter is often used for noise smoothing[12]. Removing the first IMFs, after EMD decomposition, filter out ecg noise while preserving QRS content [13, 14]. In this work, we have combined the advantages of EMD filtering (one run approach for low and high frequency noise) and 6th order band-pass Butterworth filter (noise smoothing). We subtract the first IMF (IMF_1) to remove the high frequency and apply the Butterworth filter to smooth the signal.

2.2. Neural Network

A neural network is a mathematical function, see the picture 2[4].In this paper, we propose a neural network (figure 3) composed of sixteen nodes. To set up a neural network, there must be defined the input data, the activation function and the thresholds of the nodes. Each data is associated with a weight.

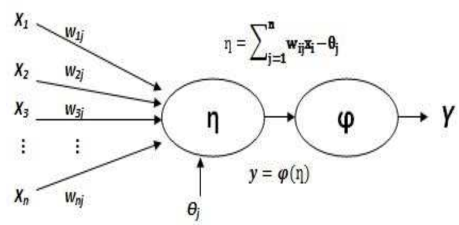

Figure 2. *Representation of an artificial neuron [4]. Inputs are multiplied by their weight. The products are added to give the weighted sum. The threshold of the node is subtracted from the weighted sum to determine the output of the node.*

3. ECG patterns detection

Intrinsic parameters are used for ECG patterns detection that can lead the classification and prediction that will be further performed. Indeed, statistical properties(mean, variance, standard deviation, energy and power) are often used as input parameters for classification [4]. However these parameters are global descriptors of data. Unlike statistical properties, morphological and frequency attributes allow local analysis. Thus, in this work, we used a set of morphological and frequency properties (negative form, maximum amplitude, minimum amplitude, maximum width, minimum width, hearth rate, and hearth rhythm) of the ECG and the Heaviside activation function for classifying and predicting the arrhythmia.

3.1. Parameters Vector

The parameters vector is used as the neural network entry. It is composed of an electrocardiogram's properties.The parameters processing are performing as follows :

1) Input : ECG
2) detect the negative form
3) compute QRS complex width and amplitude
4) apply min and max function on width and amplitude

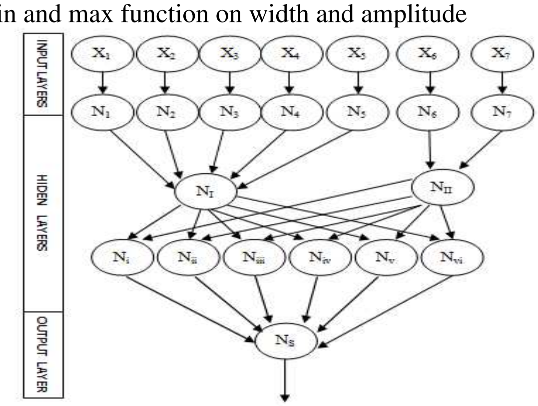

Figure 3. *Architecture of the neural network. The variables X_1 ... X_7 represent the morphological and frequency properties, respectively the negative form, the maximum amplitude, the minimum amplitude, the maximum width, the minimum width, the hearth rate and the hearthbeat. The variables N_1 .. N_{vi} represent the intermediate nodes. The Node N_s determines the arrhythmia type.*

5) compute hearth rate and hearth rhythm

6) Output : return a parameters vector

Detailed description of the QRS complex detection, width and amplitude computations were presented in [4]. The hearth rhythm regularity detection requires a certain number of steps :

1) identify the R-waves

2) count the R-R intervals

3) compute the R-R regularity rate

4. Arrhythmia Classification

The classification involves two functions : the network function and the classifier function. The implemented neural network uses H(x),the step activation function with a threshold (s) for each parameter : $H(x) = 0 \; if \; x < s \; and \; H(x) = 1 \; if \; x \geq s$. The parameters are negative form, minimum width, maximum width, minimum amplitude, maximum amplitude, hearth rate and hearth rhythm which are respectively associated to the following thresholds 0, 0.06, 0.10, 0.5, 2.5, 50, 110 and 10 [10]. The network function is composed of sixteen neurons. It takes as input a parameter vector and returns one of these six classes : Class 0 : normal,Class 1 : sino-auricular node dysfunction,Class 2 : supra-ventricular tachycardia,Class 3 : ventricular tachycardia,Class 4 : auricular flutter and Class 5 : Auricular Fibrillation.

5. Arrythmias Prediction

From our knowledge, the few works that have been done for hearth rhythm prediction are based on linear model. However real world phenomena are not linear. This work is one of the first step for the development of an efficient model for ECG predictive analysis. The proposed approach is based on the exponential non-linear regression model. This estimation is done through the following equation

$$y = b_1 + b_2 * x^{b_3} \qquad [2]$$

where, y is the estimated frequency, x the prediction horizon and $b_{1,2,3}$ are the model coefficients. The frequency prediction is done such as :

1) computation of the 10 previous hearth rates,

2) estimation of the hearth rate,

3) classification of the estimated cardiac frequency,

4) prediction of an arrhythmia.

The prediction base is constructed by extracting the samples from last 10 minutes and computing the corresponding hearth rates. The cardiac frequency is estimated using the algorithm 1.

Tableau 1. *ECG classified*

CLASS	ECG
Sino-auricular node dysfonction	103, 105,107, 108, 114,115,119,121,123,201,202
	208,210,213,220,222,223,228,231,233,234
Supra-ventricular tachycardia	102,111,215
Ventricular tachycardia	101
Auricular fluter	204,209
Auricular fibrillation	113, 118, 217

Algorithm 1 Prediction Method

```
function predire(f,t,th)
modelfun ← @(b,x)b(1) + b(2) * x(:,1).^b(3)
beta0 ← [111]
mdl ← Estimate(t,f,modelfun,beta0)
fp ← predict(mdl,th)
return fp
```

The function (algorithm 1) takes ten previous frequencies(f), time samples (t) and th (horizon prediction). It estimates the hearth rate at th (prediction horizon).

6. Results and discussion

To illustrate the classification and prediction of arrhythmias, we have used the MIT-BIH ECG database [4, 15]. MIT-BIH Arrhythmia is a waveform and a class completed references databases of physionet.org composed of 48 signals recorded on a half-hour that can be downloaded from physionet.org.

6.1. Classification

We first use dual filtering based on the EMD and the Butterworth filter during the pre-processing step. Then, we compute the parameters for anomalies detection and arrhythmia classification, and estimate the hearth rate for the arrhythmia prediction. We have the following results : 8 Abnormal ECG was detected as abnormal and 1 abnormal ECG was detected as normal(detection error) ; 4 normal ECG were detected as abnormal (detection error) and 2 ECG normal ECG were detected as normal.The detection method achieved a performance rate of 88.89% with an error rate of 11.11%. The performance indices are : Accuracy (66.67%), Sensitivity (66.67%), Specificity (88.89 %) and Positive predictive (33.34%). The performance of anomalies detection is represented by the specificity. After the anomalies detection, if an anomaly is detected then the system continues with the arrhythmia classification else it continues with arrhythmia prediction. The classification result is presented in the table 1.

Compared to the results presented in [4], there is an improvement in performance of 5.56% (83.33 % to 88.89%). The same trend is noted for the back propagation method (83.40%) proposed in [16] and ANN based classification (87.50%) proposed in [17]. The noted improvement is due to the use of the morphological and frequency parameters. Besides, these parameters allow local analysis with defined thresholds.

6.2. Prediction

If an anomaly isn't detected then the system continues with the proposed non linear regression based arrhythmia prediction (algorithm 1). An estimated hearth rate at prediction horizon $t = 11$ is used to predict an arrhythmia. To validate our model, the data were tested with the linear model and compared with the proposed non linear model. The image 4 shows the results of the prediction with the two models in relation to the calculated heart rates.

The linear prediction predicts correctly twelve EGC and the non-linear prediction pre-

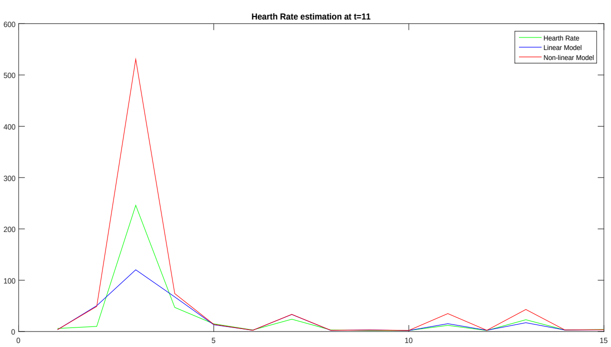

Figure 4. *Hearth Rate estimation*

dicts correctly thirteen ECG. The performance rate of the linear and non-linear model are respectively 80.00% and 86.67%. Thus there is an improvement in the prediction accuracy using the proposed model.

7. Conclusion

In this work, we proposed an approach based on empirical mode decomposition(EMD), the neural network, and non-linear regression for classification and prediction of arrhythmia. The main contributions are the ECGs morphological and frequency properties taken as input during the classification and the predictive model based on hearth rate analysis. The output of our approach gives promising results for the classification and prediction of arrhythmia. Future works will focus on modeling the neural network with a filter bank and the implementation of a secure online system for classification and prediction that can be used by practitioners as help for decision support.

8. Bibliographie

[1] SOTT PURDY, ZUHA AGHA, SABUTAI AHMAD, ALESADER LAVIN, « Unsupervised real-time anomaly detection for streaming data », *Neurocomputing*,262 :134-147, 2017.

[2] L. MESIN, « Heartbeat monitoring from adaptively down samples electrocardiogram », *Computers in Biology and Medecine*,84 :217-225, 2017.

[3] S.SAHOO, B. KANUNGO, S. BEHERA, S.SABUT, « Multiresolution wavelet transform based feature extraction and ECG classification to detect cardiac abnormalities », *Measurment*,108 :55-66, 2017.

[4] A-DALIBOU ABDOU, NDEYE FATOU NGOM, SAMBA SIDIBE, OUMAR NIANG, ABDOULAYE THIOUNE, CHEIKH H.T.C NDIAYE, « Neural Networks for biomedical signals classification based on empirical mode decomposition and principal component analysis », *Lecture Notes of the Institute for Computer Sciences, Social Informaticq and Telecommunications Engineering (LNICST). ISSN 1867-8211. pp. 267-278*, 2017.

[5] V.GUPTA, M. MITTAL, « KNN and PCA classifier with autoregressive modeling during different ECG signal interpretation », *Proc. Comp. Scienc*,125 :18-24, 2018.

[6] K.N. RAJESH, R. DHULI, « Classification of ECG hearthbeats using nonlinear decomposition methods and support vector machine », *Computers in biology and medecine*,87 :271-284, 2017.

[7] K.M ATOUF, A. ISSAM, A. MOHAMED, B. ABDELLATIF, « ECG image classification in real time based on harr like features and artificial neural networks », *Procedia Computer Science* ,73 :32-39, 2015.

[8] J.A. GUTIERREZ-GNECCHI, R. MORFIN-MAGANA , D. LORIAZ-ESPINOZ , A.C. TELLEZ-ANGUIANO, E. REYES-ARCHUNDIA, A. MENDEZ-PATINO, R. CASTANEDA-MIRANDA, « DSP based arrythmia classification using wavelet transform and probabilistic neural network », *Biomedical Signal Processing and Control*,32 :44-56, 2017.

[9] M.L. TALBI, P. RAVIER, « Detection of PVC in ECG signal using fractional linear prediction », *Biomedical Signal Processing and Control*,23 :42-51, 2016.

[10] R. DUBOIS, « Application des nouvelles méthodes d'apprentissage pour la détection précoce d'anomalies cardiaques en électrocardiographie », *PHD Université Pierre et Marie Curie - Paris VI*, 2004.

[11] S. PAL, M. MITRA, « Empirical mode decomposition based on ECG enhencement and QRS detection », *Computers in biology and medecine*,12 :83-92, 2012.

[12] H. ZHANG, « An improved QRS wave group detection algorithm and matlab implementation », *Physics procedia*,25 :1010-1016, vol. n^{o} , 2012.

[13] R. RODRIGUEZ, A. MEXICANO, J. BILA, S. CERVANTES, R. PONCE, « features extraction of electrocardiogram signals by applying adaptative threshold and principal component analysis », *Journal of applyied research and technology*,13 :261-269, 2015.

[14] Z.H. SLIMANE, A. NAIT ALI, « QRS Complex detection using empirical mode decomposition », *Digital signal processing*, 20 :1221-1228, 2010.

[15] GB MOODY, RG MARK, « The impact of mit-bih arrhythmia database », *IEE Eng in Med and Biol*, 20 :45-50, 2001.

[16] J.FENG, « ECG Classification based on feature-extraction and neural network », *Phd, Sichuan Normal University*, 2005.

[17] C.ALEXAKIS, H.O NYONGESA, R. SAATCHI, N.D. HARRIS, C. DAVIES, C. EMERY, R.H IRELAND, S.R HELLER, « Feature extraction and classification of electrocardiogram (ECG)signals related to hypoglycaemia », *Proc. Comput. Cardiol.*,30 :537-540, 2003.