Electrocardiogram Classification Using Wavelet Transformations

Iurii Krak,
Taras Shevchenko National University of Kyiv
Kyiv, Ukraine
krak@univ.kiev.ua

Anatolii Pashko,
Taras Shevchenko National University of Kyiv,
Kyiv, Ukraine
aap2011@ukr.net

Oleg Khorozov,
Glushkov Institute of Cybernetics of NAS of Ukraine,
Kyiv, Ukraine
oleh753@hotmail.com

Oleg Stelia
Taras Shevchenko National University of Kyiv,
Kyiv, Ukraine.
oleg.stelya@gmail.com

Mykola Efremov
Taras Shevchenko National University of Kyiv,
Kyiv, Ukraine
gleibeffrime@gmail.com

Abstract— **The work investigates the continuous and discrete wavelet transform to determine the corresponding features of ECG signals with variable temporal and spatial components. Discrete wavelet transform is implement as a filter bank. The approximation and refinement of wavelet coefficients from different frequency sub-bands are used to eliminate high-frequency noise, compress the signals, and there classification. Continuous wavelet transform, presented in the form of a scale diagram, is using to analyse ECG signals and develop a predictive model.**

Keywords— discrete and continuous wavelet transform, neural networks, electrocardiograms, classification

I. INTRODUCTION

Most cardiovascular diseases can be prevent by timely diagnosis of cardiac arrhythmias. Atrial fibrillation (AF) is the most common tachyarrhythmia of the heart and is associated with an increased risk for stroke and heart failure. A key issue in diagnosing the type of arrhythmia is the use of expert knowledge to interpret changes in the morphology of the cardio-logical cycle and heart rhythm abnormalities. Diagnosis of various types of cardiac arrhythmias using machine-learning methods will help cardiologists determine the diagnosis for the selection of preventive measures. The study aim is to create an online classifier that will provide an analysis of the ECG signals. One solution is to use neural network models to classify the type of arrhythmia along with the choice of cardiac cycle characteristics. There article proposes to automate the process of features mapping from time-frequency domain for ECG signals classification.

The reliability of the results verified on basis of the PhysioNet ECG Dataset, which contains ECG measurements of persons indicated as Normal sinus rhythm (NSR) and persons with an arrhythmia (ARR) or a congestive heart failure (CHF). This dataset contains 96 ARR, 36 NSR and 30 CHF measurements that used to evaluate the effectiveness of the proposed method [1].

The purpose is to estimate the accuracy of predictions in anomalies of electrocardiogram signals detecting and classify the type of cardiac arrhythmia. Most biological systems reflect their normal or abnormal processes by nonstationary signals and thus joint time-frequency analysis of the physiological signals has potential applications.

The challenge is to identify relevant features of ECG signals with variable time and spatial components. In work, the deep learning architecture model for ECG signals classification is present.

II. ECG SIGNAL DATASET ANALYSIS

A hybrid network was proposed combining neural networks and wavelets transforms to identify ECG classes. Convolution neural network is linked to Wavelet transform with model “neuron” and convolution filter. The method is based on the use of wavelet functions in neural networks, which allowed the network to have better adaptability in the learning process, taking into account the translation parameters and scaling of wavelet functions. Evaluation of the results obtained by the wavelet network is satisfactory in relation to other neural networks in terms of the rate of classification of heart contractions. The combination of neural networks with wavelet functions made it possible to identify the strengths of neural models and the multilevel wavelet analysis technique. The proposed method can be considered as an effective method for classifying heart rhythm disorders with an accuracy of more than 98 %.

The most complete way to display information is to perform spectral analysis. Wavelet transform provides a general method that can be used to process signals. Various

2020 IEEE 15th International Conference on Advanced Trends in Radioelectronics, Telecommunications and Computer Engineering (TCSET) 978-1-7281-5566-1/20/$31.00 ©2020 IEEE 10.1109/TCSET49122.2020.235573

properties can be calculated and processed in the compressed area using wavelet coefficients. We can apply the wavelet transform to the ECG signal and convert it to wavelet coefficients. The coefficients characterize the behavior of the ECG signal, and the number of these coefficients is less than the amount of the original signal. This reduction in feature space is important for recognition and diagnosis.

ECG signals from mobile devices can be using for person authentication in remote access systems such as remote healthcare systems [2, 3].

III. Discrete Wavelet Transform

The wavelet transform is used to analyze data with temporal or spatial features. The wavelet transform is used to search for similarity in time series, classify and cluster time series, and identify anomalies in the behavior of time series.

Discrete wavelet transform operates with discrete parameter values. The basis of space are defined as

$$\psi_{m,k}(t) = a^{\frac{m}{2}}\psi\left(a^{m}t-k\right), \quad m,k \in Z, \tag{1}$$

where $\psi(t)$ - parent wavelet.

For practical use, there are convenient wavelets built on the basis of Gauss function and its derivatives. They have the best localization in both the time and frequency domains. The value of a can be arbitrary, as a rule, use $a=2$. In this case, the transform is called the dyadic wavelet transform. Forward Wavelet Coefficients ($s(t)$ - continuous signal):

$$W_{m,k} = \int_{-\infty}^{\infty} s(t)\psi_{m,k}(t)dt. \tag{2}$$

The inverse discrete wavelet transform has the form $s(t)=\sum_{b=-\infty}^{\infty}\sum_{л=-\aleph}^{\infty}W_{m,k}\psi_{m,k}(t)$. The number of m – parameter coefficients determines the level of signal decomposition.

For the inverse wavelet transform, use the following representation:

$$s(t) = \sum_{л=-\infty}^{\infty} C_k\varphi_k(t) + \sum_{b=-\infty}^{\infty}\sum_{л=-\aleph}^{\infty} W_{m,k}\psi_{m,k}(t), \tag{3}$$

where C_k - scaling coefficients or approximation coefficients, $W_{m,k}$ - wavelet coefficients of signal detail.

The wavelet analysis algorithm:

Let a time series be given: $s_k = s(t_k), \quad k=0,1,...N-1$.

1. Center the row and exclude trends.
2. Assess the variance, evaluate the correlation function.
3. The values of the coefficients are determined by the formulas.

$$W\left(a_i,b_j\right)=\frac{1}{M\left(a_i,b_j\right)}\sum_{k=0}^{N-1}s_k\psi\left(\frac{t_k-b_j}{a_i}\right),$$

$$M\left(a_i,b_j\right)=\sum_{k=0}^{N-1}\exp\left(-\frac{1}{\sigma}\left(\frac{t_k-b_j}{a_i}\right)^2\right). \tag{4}$$

4. Discretization of arguments:

$$a_i = a_{\min} + i\Delta a, \quad i=0,1,...N_a-1, b_j = j\Delta b, \quad j=0,1,...N-1.$$

5. The value of the scaleogram in each node is calculated by the formula:

$$S(a_i,b_j) = \left|W\left(a_i,b_j\right)\right|^2. \tag{5}$$

In [4-16], both theoretical aspects of the wavelet transform and the practical application of wavelet analysis in various fields were considered/

Let us applying discrete wavelet transform (DWT) as a filter cascade for ECG signals. A filter bank means dividing a signal into several frequency sub bands for use in applications. First, we apply a small scale corresponding to high frequencies. Then the scale increases by a factor of two (frequency decreases by a factor of two) and so on. We are using «pywt.dwt» library for decomposition signal into frequency bands. The DWT used to split a signal into different frequency sub-bands, as many as needed. If the different types of signals exhibit different frequency characteristics, this difference should be exhibit in frequency sub-bands. If we generate features from each of the sub-band, set the collection of features as an input for Logistic Regression, Random Forest or Gradient Boosting classifiers and train it, the classifier should be able to distinguish between the different types of signals:

A. Decomposition of signal into frequency sub bands

Representation of high pass and low pass filters applied to the signal with Symlet wavelet coefficients (see Fig.1). Discrete wavelet transform is implement as a filter bank. Approximation and detail coefficients from different frequency sub-bands are using in applications to remove high-frequency signal noise, signal compression, and signal classification of different types [17].

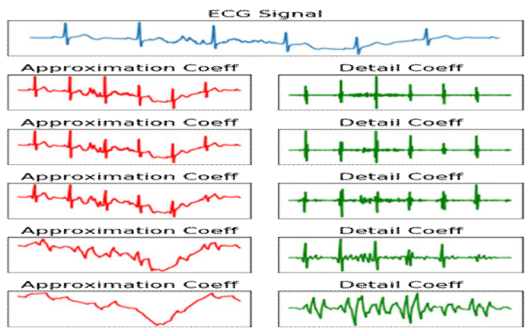

Fig. 1. Wavelet Transform Coefficients.

Signal reconstruction (fig.2):

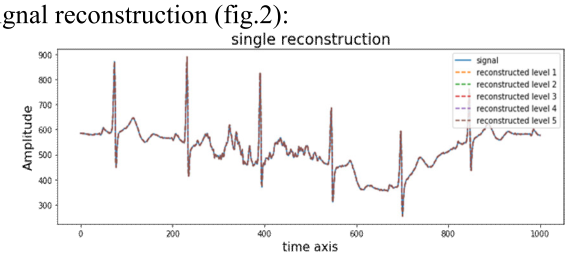

Fig. 2. Recovered signal.

Generate signal traits for each frequency range: Autoregressive value of model coefficients; Entropy as a measure of signal complexity; Statistics: variance, median, root mean square amplitude, average value of the derivative; etc. After features computation we apply the result combining function, which returns a set of N attributes. If you spread the signal into five sub bands, and create functions for each sub band, you get 5*N features per signal [17].

B. ECG Classifications

Use of DWT to decompose signals from a training set into sub bands, calculate "features" for each sub band, use "features" to prepare the classifier, and use the classifier to predict signals from the test set for time series. We apply a DWT to signals from the ECG dataset, which returns a list of coefficients. For the coefficients, for each frequency sub band, the "features" will be calculate using the defined functions. The calculated "things" are combined into a "feature vector", because they belong to a single signal. For practical implementation, DWT calculated over a sampled time-band grid. Sampling involves the approximation of the transformation on a grid of scales and positions. The wavelet transform approximated at each time step of the wavelet scale. We used DWT and «Gradient Boosting Classifier» from the «scikit-learn» library and get result: Test Score is 0.9315384615384616.

IV. Continuous Wavelet Transform and Convolutional Neural Network for Signal Classification

There are many machine learning (ML) solutions, which can be using for analysing and classifying ECG data. One of the proposing solution is to use deep learning architectures where convolutional layers behave as feature extractors for ECG classification.

Wavelet transforms have found engineering applications in computer vision, pattern recognition, signal filtering and most widely in time series measurements. Should be noted, then Wavelet transform is more performant technique than Fourier transform when frequencies of the signal vary in time and can be used to distinguish different types of signals produced by a system. It's allows to explore the frequency domain of the signal as an image by forming the result as an scaleogram and then take advantage of image classification techniques.

With a convolution neural network (CNN) it is possible to get a model which distinguish and detect different type of signals. This is allows to explore the frequency domain of the signal as an image by formatting the result as a scaleogram and then take advantage of image classification techniques. With CNN we get a model which quickly allows to detect a healthy person from others with heart disease. The ECG measurements of person with a healthy heart and person with arrhythmia will have different scaleograms. Based on ECG data, we made a classification over three groups of people with different pathologies: cardiac arrhythmia, congestive heart failure and healthy people (Fig.3) CNN automatically detect the class each scaleogram belongs to and classify them. Visualization of ECG data and label list (from MatLab).

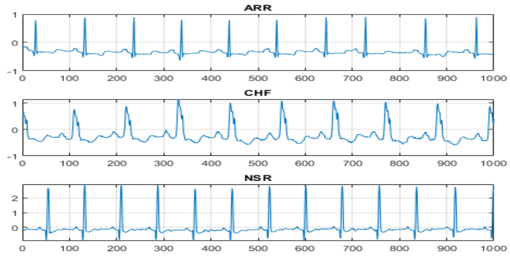

Fig. 3. Types of the classified signals

A. Analysis of a time series of the sensors data

The scalogram of the continuous wavelet transform (CWT) of a signal is a function of time and frequency (fig.4). The wavelets can be using for analyzing content of the signals because they are localized in both frequency and time. They allows to identify areas where the signal changing frequency content. It is can be useful for identifying signals with low-frequency components or frequency localization when changing frequency content. The Wavelets are using to localize transients when changing the content of ECG signals components.

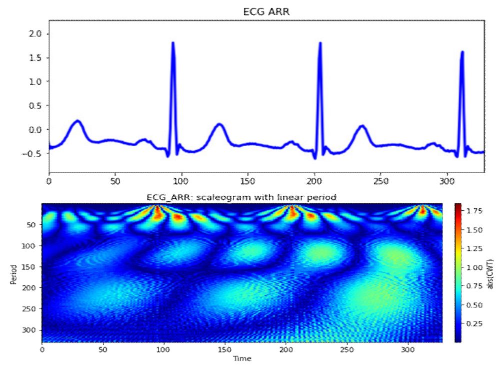

Fig. 4. Signal and its wavelet transform.

We utilize Wavelet transform for filtering and analysis ECG signals with CNN architecture to develop a predictive model to indicate normal or abnormal behavior. Frequency spectrum of ECG signal is in the range from 3 to 45 Hz. Compute CWT transform using the complex Morlet wavelet and 32 scales between 3Hz and 45Hz. We can get 32 channels with base line flattening.

Training the ECG classifier with scaleograms was provided a sequential model (see Tabl.1)

TABLE 1

Layer (type)	Output Shape	Parameters
flatten (Flatten)	(None, 195075)	0
dense (Dense)	(None, 300)	58522800
dense_1 (Dense)	(None, 100)	30100
dense_2 (Dense)	(None, 3)	303

Here: total and trainable parameters: 58,553,203.

To analyze the change in the signal morphology for arrhythmia (ARR) examples using the Morlet wavelet transform. Each horizontal characteristic in the scaleogram is a frequency of the signal. The scaleogram can be understand as image and apply neural network model to train a classifier. After running 10 epochs using a stochastic gradient descent as optimizer, and computing the loss with a sparse categorical cross-entropy, the accuracy metric shows a good performance. We get accuracy of 96% on the ECG dataset.

V. Heart Rate and Cardio Signal Monitor

An electrocardiogram (ECG) displays a series of waves used to identify heart rhythm disorders. Heartbeat disorders are grouped into two main categories: bradycardia, tachycardia. In some cases, the beat may also break up into separate waves that circulate randomly through the heart muscle (myocardium), a phenomenon known as fibrillation. The RR-interval is used to calculate the instantaneous heart rate. The thresholds was determined by an Arduino microcontroller to detect R-peaks, thereby calculating heart rate. The ECG signal obtained after passing through the cascade of the filters was visualized using a serial Arduino plotter. The signal was sampled at a frequency of 200 Hz. The assembled circuit is powered by a battery that makes the prototype a portable.
An abnormal heartbeat is indicated and recording. The placement of the electrodes occurs along the axis of alignment of the heart

A. *Signal filtering*

The ECG input has many artefacts that need to be filtered. The main sources of ECG noise are baseline deviation (low frequency noise), transmission line interference (60 Hz noise), muscle noise (electrical muscle activity - electromyography) for interference from other equipment. We use a high pass filter (cut 0.05 Hz) to remove the base noise, and a low pass filter to filter out unwanted frequencies in the ECG spectrum. The Arduino module has been programmed to operate as an IIR notch filter with a bandwidth of 2 Hz. Cut-off frequencies are 48 Hz and 52 Hz. $Y = 0.6022*X - 0.6022*X1 + 0.6022*X2 + 0.6022*Y1 - 0.2043*Y2$, where X is the output of the low pass filter, and Y is the output of the notch filter. Heart rate fluctuation chart (Fig.5):

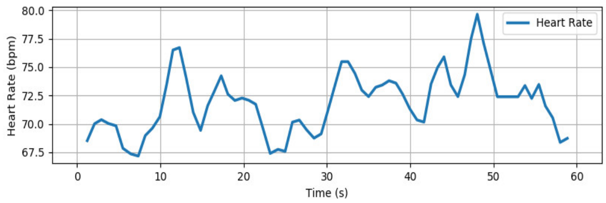

Fig. 5. Heart rate

After the monitoring results are received, the information should be transferred to the server of the diagnostic centre for analysis and formulation of the annotation. Random noise exists in wearable sensor based measurements whose frequency spreads. Frequency filtering or smoothing is very likely damage critical information such as QRS. Remove noise from heartbeat using a trained auto encoder could be a promising direction. The auto encoder is trained using noisy heartbeat as input and corresponding ground truth heartbeat as output. Noise is modelled as uniform distribution. The signals used in the example are sampled at 200 Hz.

VI. Conclusion

Electrocardiography is used to help diagnose various heart conditions by ECG signal monitoring. The use of wavelet transform allows the analysis of the cardiogram and received the necessary parameters for diagnose various heart conditions. This study is an ECG signal classification using Deep learning methods and maintaining an online database for remote access.

A further result of the research will be the use of wavelet analysis for heart conditions monitoring using mobile devices and emerging technique based on artificial neural networks.

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