Physiological Signals Analysis, Recognition and Classification Using Machine Learning Algorithms

Iurii Krak[1,2 [0000-0002-8043-0785]], Anatolii Pashko[1[0000-0001-6944-8477]],
Oleg Khorozov[2[0000-0001-8812-323X]], Oleg Stelia[1[0000-0002-1453-501X]]

[1]Taras Shevchenko National University of Kyiv, 64/13 Volodymyrska str., 01601, Ukraine
yuri.krak@gmail.com, aap2011@ukr.net, oleg.stelya@gmail.com
[2]Glushkov Cybernetics Institute, Kyiv, 40 Glushkov avenue, 03187, Ukraine
oleh753@hotmail.com

Abstract. The spatial and time-frequency domain features analysis are major approaches for signal classification. For non-stationary signals classification, the selection of features is paramount to the robustness of the recognition systems. Among machine learning algorithms, convolutional neural networks (CNNs) have achieved significant performance in many pattern recognition tasks, along with traditional approaches such as Random Forest or Gradient Boosting. Wavelet transformations allow utilizing spectral components that are useful in signal processing tasks. The performance of the wavelet applications for signal classification was evaluated. The experiments show that wavelet transformations can achieve better accuracy than existing algorithms while having significantly fewer parameters than conventional CNNs.

Keywords: machine learning, classification, signal analysis, expert systems, wavelet transformation

1 Introduction

The primary diagnosis of cardiovascular disease involves expert systems based on the rules of solving medical problems. Rule-based Expert systems are inefficient using big data because they are hard to scale in the presence of new data. Therefore, automating data analysis and recognition procedures is required.

Electrocardiography (ECG) as a non-invasive method for diagnosing the cardiovascular system, involves the identification of morphological features characterizing the types of a heart disability. The data getting from patients monitoring potentially contain a lot of information used inefficiently due to the heterogeneous data structure, which is difficult to interpret. One solution is to use a deep learning model to classify the type of arrhythmia along with the choice of cardiac cycle characteristics.

The deep learning architecture model with the wavelet convolutional layer for signals classification is presented in this work. The reliability of the results verified on the basis of the ECG database, which was used to evaluate the effectiveness of the pro-posed method. The article proposes to automate the process of features selected

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CEUR-WS.org/Vol-2608/paper71.pdf

from the time-frequency domain for ECG signals online classification using machine learning models. ECG signals from mobile devices can be using for person authentication in remote healthcare systems [1, 2]. The purpose is to recognize the cardiovascular disease and estimate the accuracy of predictions using deep learning methods for ECG signals classification. A software framework that facilitate integration of the mathematical models and computer simulations make it possible to efficiently classify and predict the status of patients. The proposing solution is to use the wavelet convolutional layer for feature extractors and the neural network are used for making a final decision.

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.

2 ECG signals analysis using wavelet transformations

The ECG signals contain many artifacts that need to be filtered. The main sources of ECG noise are baseline deviation (breathing bias), muscle activity (contraction), poor electrode contact, and high-frequency network interference from equipment. Baseline wander elimination is considered as a classical problem in ECG signal filtering during data collection. The ECG data cleaning step is necessary since a signal with noise reduces the accuracy of diagnosis. The wide variety of ECG signals waveforms. The purpose of signal processing is to eliminate low-frequency drift of the signal baseline and high-frequency noise. Many studies have developed linear or non-linear filters to remove additive noise and interference, such as moving averaging filters, low-pass filters, band-pass filters, non-linear filters and Savitsky-Golea smoothing filters. Wavelet-based noise removal methods are connected by wavelet coefficients for filtering high-frequency noise and baseline drift effects [3].

To analyse and verify the reliability of the results, the PhysioNet ECG dataset [4] was used, which contains ECG measurements for individuals labelled Normal Sinus Rhythm (NSR) and those with arrhythmia (ARR) or congestive heart failure (CHF). This data set contains 96 ARR, 36 NSR and 30 CHF records, which were used to evaluate the effectiveness of the proposed method. Based on ECG data, a classification over three groups of people with different pathologies: cardiac arrhythmia, congestive heart failure and healthy people was made.

2.1 ECG signals analysis using discrete wavelet transformations

The wavelet transform is used to analyse data, search for similarity in time series, classify and cluster time series, identify anomalies in the behaviour of time series.

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

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

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:

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

$s(t)$ - continuous signal.

The inverse discrete wavelet transform has the form $s(t) = \sum_{\text{Ь}=-\infty}^{\infty} \sum_{\text{Л}=-\aleph}^{\infty} W_{m,k}\psi_{m,k}(t)$.
The number of m - parameter coefficients determines the level of signal decomposition. For the inverse wavelet transform, use the following representation:

$$s(t) = \sum_{\text{Л}=-\infty}^{\infty} C_k \varphi_k(t) + \sum_{\text{Ь}=-\infty}^{\infty} \sum_{\text{Л}=-\aleph}^{\infty} W_{m,k}\psi_{m,k}(t),$$

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

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

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 scalogram density in each node is calculated by the formula:

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

Theoretical aspects of wavelet transform have been considered in works [5-7], the use of wavelet transform in vibration studies in works [8-9], identification of systems [10], fuzzy models [11-12].

In [13-19] various problems were analyzed when processing signals using wavelet transform and convolution neural networks.

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:

2.2 ECG signals analysis using continuous wavelet transformations

The continuous wavelet transform (CWT) of a signal can be using for analysing 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 signals components.

Wavelet transform provides a general method that can be used to process signals. Various properties can be calculated and processed using wavelet coefficients. We can apply the wavelet transform to the ECG signal and convert it to wavelet coefficients. The coefficients characterize the behaviour 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.

A classification algorithm using a wavelet transformation for ECG signals is proposed. The wavelet transform is used to analyse spatial signal and identify anomalies in the behaviour of time series. The algorithm used morphological filtering and wavelet transform with a selected mother wavelet. The wavelet coefficients denotes the correlation between the signal and the wavelet in the given scale and position. The optimal wavelet should have a shape identical to the signal being analyzed. Continues wavelet transform is used to evaluate how much a signal resembles a scaled and translated mother wavelet.

The wavelet transform of a time-continuous signal $x(t)$ is defined as:

$$CWT\ (a,b) = \frac{1}{\sqrt{a}} \int x(t)\psi^*\left(\frac{t-b}{a}\right)dt\ ,$$

where $\psi^*(t)$ is the complex conjugate of wavelet function, a – scale, b - translation parameters respectively. The function $\psi(t)$ compresses or dilates depending on a, which enables the CWT to extract the low- and high- frequency components of $x(t)$. The wavelet scale a characteristic frequency's of the wavelet such as the spectral peak frequency, pass band centre, and central frequency. The original signal $x(t)$ may be reconstructed using an inverse transform.

The frequency associated with a wavelet of arbitrary a scale is given by $f = \frac{f_c}{a}$, where the characteristic frequency of the mother wavelet (scale $a = 1$ and location $b = 0$), f_c becomes a scaling constant and f is the frequency for the wavelet at arbitrary a-scale. The contribution to the signal energy at the specific a scale and b location is given by the two-dimensional wavelet energy density function known as the scalogram.

$$S(a,b) = |W(a,b)|^2.$$

The scalogram can be integrated across a and b to recover the energy in the signal. 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. The wavelets are using to localize transients when content of ECG signals components are changed.

3 Wavelet transform for filtering and analysis ECG signals with CNN architecture

We utilize Wavelet transform for filtering and analysis ECG signals with CNN architecture to develop a predictive model to indicate normal or abnormal behavior. A signal $x(t)$ transformed Wavelet into a 2D space, are contained continuous mother wavelet $\psi(t)$ with a - scale factor and b - translation factor.

The kernel at scales = [3, 4, 5, 6] with Morlet wavelet are plotted (Fig.1).

The 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 or 64 channels with base line flattening.

A visualization of the CWT coefficients - 2D scalogram can be used to improve the distinction between varying types of a signal. To evaluate and analyze a signal morphology the Morlet wavelet transform was used, as show at the plotter below for fragment of the ECG signal (Fig.2).

Let presented the example of the spectrograms segment of the cardiac cycle with a stride in time every 10 samples with scale 32 wavelet Morlet and Baseline wander elimination (Fig. 3).

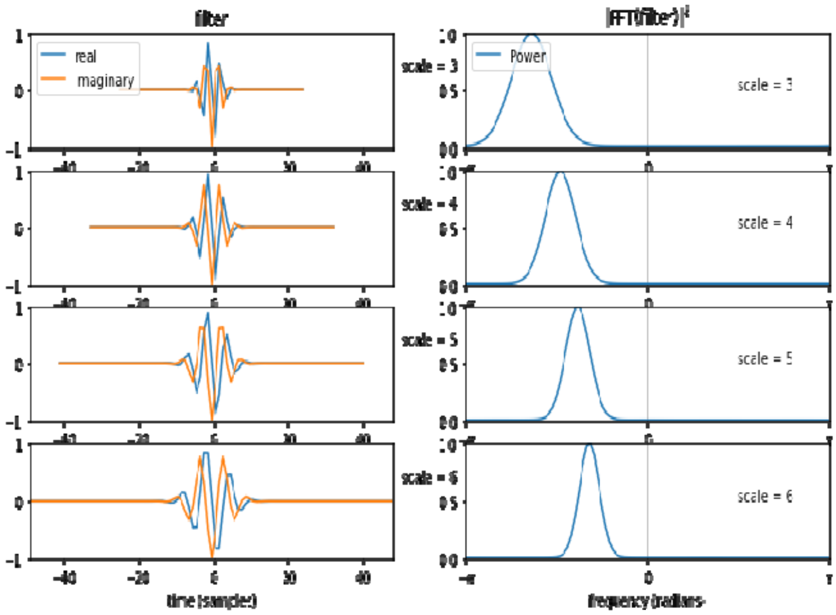

Fig.1. Morlet filters

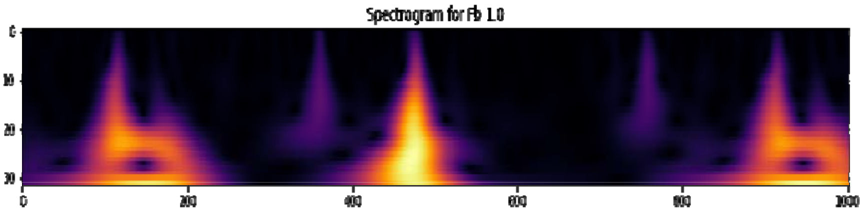

Fig.2. Segment of the cardio signals

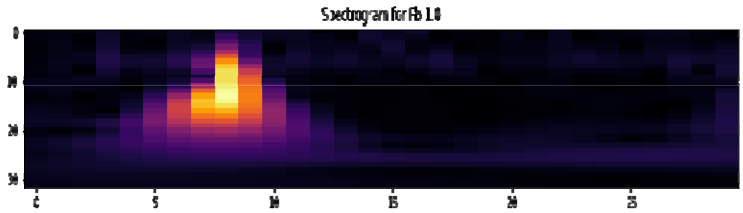

Fig. 3. ECG Cycle

The CWT consists of convolution of filter with the signal. The convolution kernels are defined by means of scales for mother wavelet. A multiscale approximation is the design method of most of the practically relevant wavelet transforms.

A time-frequency transform method and convolutional neural network was used as filtering. This formulation allows us to connect CNN with a multi-resolution analysis. We use a single-channel data set and wavelet transformation with multiple channels for using CNNs model.

4 Signal classification based on the continuous wavelet transform

A scalogram is the absolute value of the continuous wavelet transform coefficients of a signal. Since ECG signals are sensitive to noise, studies have been con-ducted by transforming signals into a frequency domain that is efficient for analysing noisy signals. The signal transforming from time domain to frequency domain, the 1-D signal becomes a 2-D matrix, and it could be ana-lysed at multiresolution. This process makes signal analysis morphologically complex and existing simple classifiers could perform poorly. We investigate the possibility of using the scalogram as input to convolutional neural networks, which exhibit optimal performance for the classification of morphological imagery. When training data is small transfer learning can be used with pretrained deep models to desision making and prognoses with scale range 32 wavelet. Time-frequency rep-resentation of the cardiac cycle using Morlet Wavelets wavelet with 120 scales. A smaller range of scales (32) enables more focus of abrupt changes in signal and a wide range of scales (64 or 128) provides more information, which can provide a better classification accuracy.

Visualization of CWT coefficients allows to distinguish cardiac cycles and QRS complexes of the ECG signal analysing [11,15]. The scalogram with 128 range of scales of the cardiac cycle data. The plots of cardiac arrhythmia and normal sinus rhythm represent below.

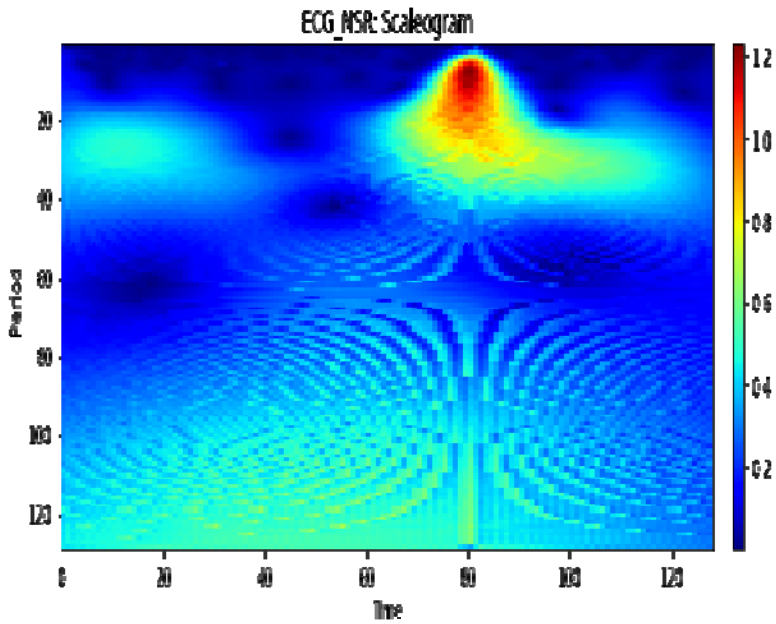

Fig. 4. Cmor0.5-1.0 ECG_NSR cycle

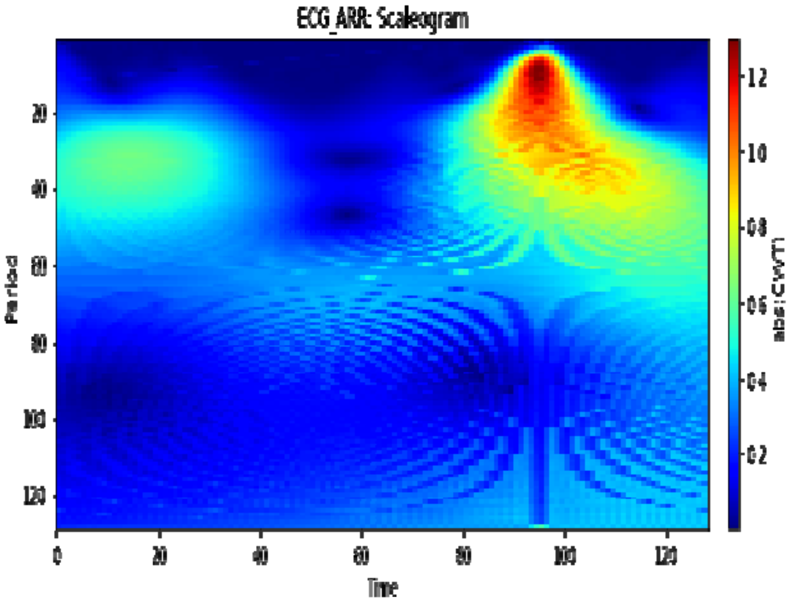

Fig.5 Cmor0.5-1.0 ECG_ARR cycle

A horizontal characteristic of the scalogram is signal frequency. The scalogram can be understand as image and apply neural network model to train a classifier. A model parameters are show in the Table 1. Sequential convolution neural network model with Trainable parameters: 58,553,203

```
num_filter, num_classes = 3, 3
model = keras.models.Sequential([
   keras.layers.Flatten(input_shape=[fs-1, fs-1, num_filter]),
   keras.layers.Dense(300, activation="relu"),
   keras.layers.Dense(100, activation="relu"),
   keras.layers.Dense(num_classes, activation="softmax")
])
model.compile(loss="sparse_categorical_crossentropy",
            optimizer="sgd", metrics=["accuracy"])
```

Table 1 Model Parameters.

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

A ‘Flatten’ layer transforms a two-dimensional matrix of wavelet convolutional features into a vector that can be fed into a neural network classifier. Training the ECG data set segments are demonstrated on the Fig.6.

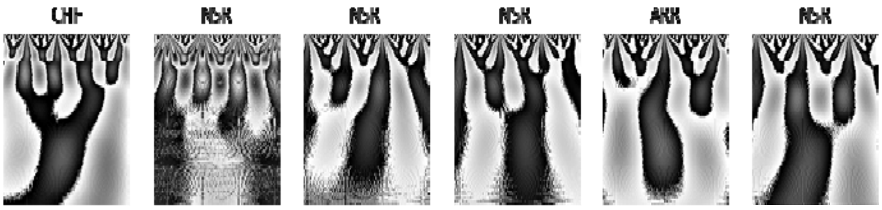

Fig.6. ECG signal segments

After running 10 epochs using a stochastic gradient descent as optimizer, and computing the loss the accuracy metrics shows a good performance. We got accuracy of 96% on the ECG dataset. Predicted label (loss: 0.1401 - accuracy: 0.9573). The results of the investigation are show on the Fig. 7.:

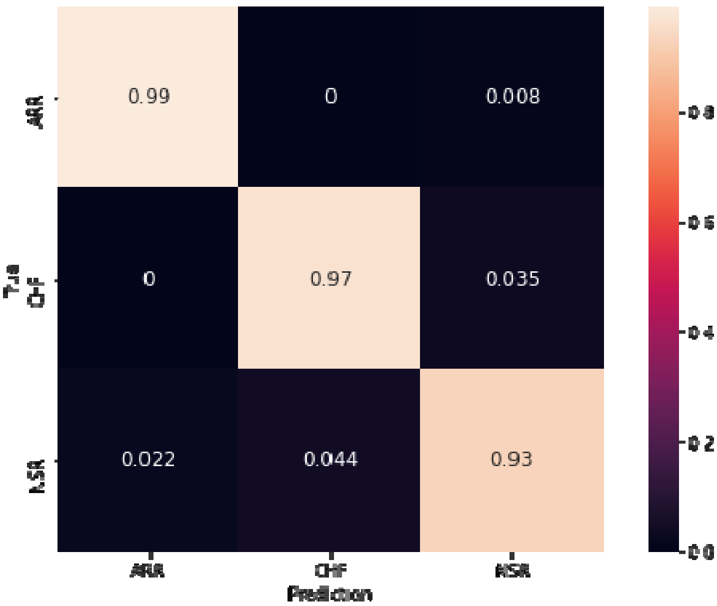

Fig. 7. Confusion matrix

With a wavelet convolution neural network we get a precise model. With a simple convolution neural network we were able to get a precise model which quickly allows us to detect a healthy person from others with heart disease. Based on ECG data a classification over three groups of patient with cardiac arrhythmia, congestive heart failure, healthy person was made. Automatic ECGs classification is useful for emergency medicine and remote monitoring as a method of disease identification.

The Wavelet transform technique allows us to explore the scalogram of non-stationary signals and then take advantage of image classification techniques.

5 Conclusion

There are many configurable model of the neural networks configurations that affect the result. Continuous and discrete wavelet transformations are superior to other non-stationary signal processing methods and classification accuracy.

The Wavelet transform technique is the most performant if the composite components of the signal vary in time. Wavelets transform signals from the time-domain to the frequency-domain and gives the spectrum. The Wavelet transform technique allows to explore the frequency domain of the non-stationary signals. The results of the CWT in combination with CNN prove that these approaches are a good choice for the classification of time series.

A neural network with wavelet cores is mainly designated for pattern recognition. Wavelet coefficients are used as input to the network.

A wavelet network usually consists of a neural network with direct connection, with one hidden layer and activation functions of which are taken from the wavelet family. Since wavelet coefficients quite effectively reflect the essence of the signal, dimensionality reduction can be achieved by wavelet processing.

Wavelet-neural networks combine the wavelet transform (decomposition-deconvolution) into one neural networks.

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