# Classification of Time Realizations using Machine Learning Recognition of Recurrence Plots

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**Abstract.** In the article,the machine learning classification of time realizations using the recurrence plot visualization is considered. Every time realization is converted intoa matrix of recurrence states and it is presented as a black-and-white image. The resulting images of realizations are classified using deep neural networks. A deep residual neural network is used as an image classifier. The binary classification of EEG realizationsnsis carried out. The result of the binary classification is the detection of an epileptic seizure. The data for the experiment are records of brain activity containing 178 values. The results of the studyshow that the considered method has a high classification accuracy. The proposed classification approach can be readily used in practice.

**Keywords:**machine learning classification, time series classification, recurrence plot, EEG realizations, deep residual networks

## 1 Introduction

One of the most difficult classification tasks is time series classification. A time series can be represented as a time realization of some dynamic system, which reflects the many internal and external relations of this system. Complex dynamic systems include biological, informational, technical, and social ones. The time series of such complex systems are partially or completely random, having an inverse nonlinear relationship and a long-term correlation dependence. A well-known example of biomedical time series is realizations of electroencephalogram (EEG).

The human brain has an electric field, which is characterized by electric surges from several milliamps to several hundred milliamps. Each neuron of the brain generates a change in electrical potential, this process can be measured. Analysis of the electric field of the brain is widely used in the diagnosis of various diseases. Thus, the task of classifying EEG realizations arises.

Currently, machine learning is widely used in time series classification. Various approaches to machine learning methods for time series classifying, including algorithms, the selection of features and applications, are considered in review papers [1-6]. It should be noted a large number of algorithms, metrics and features, which can be used for comparison and further classification of time series. In addition, many of them are highly specialized and rather cumbersome.

There are much fewer methods that allow to represent time series in the form of some structures, for example, images, which are easy to compare with each other. One of these approaches, which allows us to visualize the time series in the form of a recurrence plot, is presented in this work using the classification of EEG realizations as an example.

## 2 Literature review

Most often, after the time series preprocessing, a set of some features is extracted from it, which are the input of the classifier. The selection of features depends on the task of classification. Features can characterize various time series attributes, for example, the structure of the time series components [7], fractal [8] or chaotic [9] properties of series.

The simplest features to classify might be the values of the time series themselves. In [10–12], it was shown that in the case of strongly expressed fractal properties, it is sufficient to consider the values of the series without calculating the fractal characteristics. Also, various distance measures of the time series can be used as features [6, 13]. A popular method of feature extraction is the conversion of the time series into the frequency domain applying the Fourier or the wavelet transform [14].

The above-mentioned approaches are widely used to classify EEG realizations. The review [15] presents the majority of modern machine learning methods used to classify EEG signals. The review [16] focused on the use of deep learning for EEG classification tasks.

At the same time, in recent decades, methods of time series analysis based on chaotic dynamics methods have become widespread. The starting point, in this case, is the fact that a single time realization of a dissipative system is enough to restore its attractor, which contains all the information about the system [17]. In particular, the brain (or part of it) can be considered as a nonlinear dynamic system that is sensitive to initial conditions, and EEG is the trajectory of this dynamic system [18].

One of the methods originating in nonlinear dynamics is recurrence analysis (the method of recurrence plots), originally proposed in [19] and further developed in [20-21]. Currently, recurrence analysis is widespread and used to characterize various systems, including those with fractal properties [22–23].

The recurrence plot contains state repeatability information of a dissipative dynamical system represented by a time series. Recurrent properties can be visualized in the form of geometric structures and the time seriesdynamics may be clearly demonstrated.Thus, the technique of recurrence plots converts time series into images that can be classified using computer vision methods [24-26]. However, such studies are quite new and have not yet become widespread.

The present work aims to carry out the classification of shortEEG realizations based on the recurrence plots, which are converted into images and further classified using a residual neural network.

## 3 Time series classification based on recurrence plots

The method of recurrence plots is based on the restoration of the system attractor from single time realization (Packard-Tackens procedure) [17]. In this case, the pseudophase state space $X$ of the system can be obtained using realization values $u_t$:

$$x_i = \left(u_i, u_{i+\tau}, \ldots, u_{i+(\mathrm{m}-1)\tau}\right)$$

where $x_i$ is the value of the pseudophase trajectory at the $i$-th moment of time, $u_i$ is the value of the time realization at the $i$-th moment of time, $m$ is the dimension of the pseudophase space, $\tau$ is the time lag.

The authors of [19] proposed a method that allows mapping the $m$-dimensional pseudophase trajectory $x_i$, $i = 1,...,N$ into a binary matrix of size $N \times N$. An element with coordinates $(i, j)$ takes a value equal to 1 if the state $\vec{x}_j$ is a recurrence tothe state $\vec{x}_i$, that is, $\vec{x}_j$ falls into some given neighborhood of $\vec{x}_i$, and the element $(i, j)$ is 0 in the opposite case. Such a matrix (recurrence plot) contains information on the recurrence behavior of the time series.

The recurrence plot $RP$ is amatrix, where value $RP_{ij}$ is equal to 1 when the distance between $x_j$ and $x_i$ is less than $\varepsilon$:

$$RP_{i,j} = \Theta(\varepsilon - \| x_i - x_j \|), \quad x_i, x_J \in R^m, \; i, j = 1,...N$$

where $\varepsilon$ is the radius of the $m$-dimensional neighborhood of a point $x_i$, $\|x_i - x_j\|$ is the distance between the points, $\Theta(\cdot)$ is the Heaviside function.

Recurrent plots are easy to visualize in black and white. Then the recurrent states are displayed in black, and the rest in white. The upper part of Fig. 1 shows a realizationof a sequence of independent random variables (left) and arealization of a discrete chaotic system (right). The lower part of Fig. 1 demonstrates the recurrence plots corresponding to these time realizations. Chaotic realizations have a specific structure related to the autocorrelation properties of the system, which is reflected in the recurrence plots. It was shown in [22, 23, 27, 28] that the change in the correlation structure of a system causes the change in the topology of the recurrence plot. Thus, the analysis of recurrence plots makes it possible to classify the observed time series.

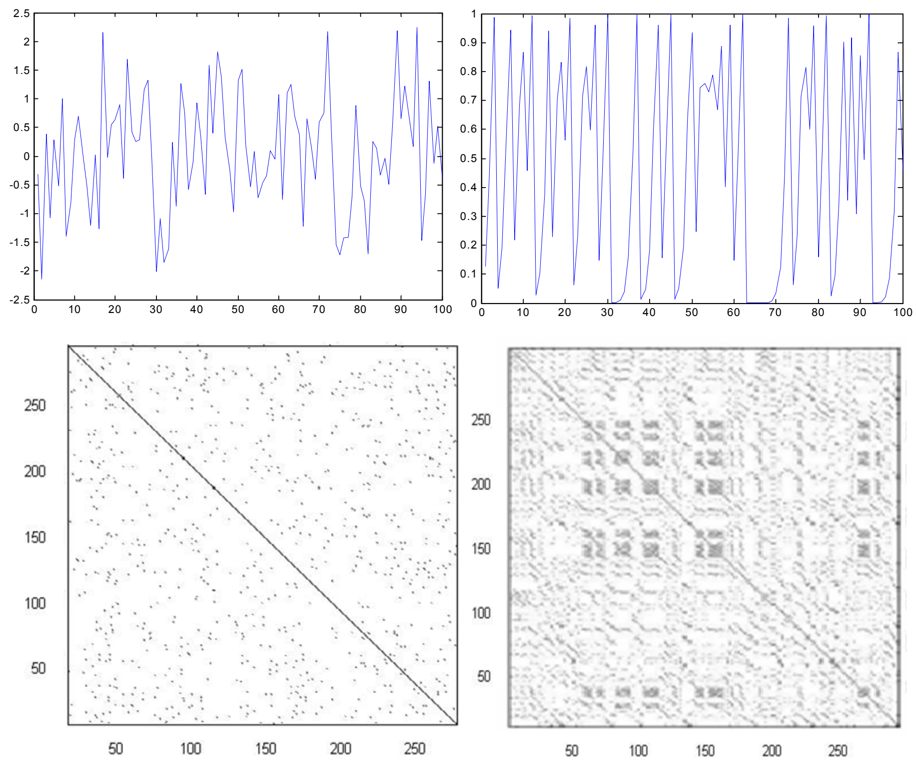

**Fig. 1.**Time realizations and corresponding recurrence plots

## 4 Input data

To carry out the classification, popular data of brain activity records were selected. The initial dataset contained records of brain activity for various human conditions: an epileptic seizure, from the tumor zone, from the healthy part of the brain, when a person has closed eyes, and when a person has open eyes. Thus, the data was divided into 5 classes. Each class contained 100 files, where each file corresponded to one object (person). Each file contained records of brain activity for 23.5 seconds, which corresponded to a time series of length 4097 values.

In [18], a detailed description of these brain activity data was given and their nonlinear properties were shown, in particular, the chaotic properties of time series corresponding to an epileptic seizure. Although the dataset contained 5 classes of time series, most studies conducted a binary classification, where the epileptic seizure class was compared with the rest. In [29], epileptic seizures were diagnosed using machine learning methods such as Artificial Neural Networks, Naive Bayesian, k-Nearest Neighbor, Support Vector Machines and k-Means. The experiment showed very good results: for most algorithms, the accuracy of the binary classification of records lasting 23 seconds was more than 99%.

A more difficult task is to determine the seizure in the case of significantly shorter data. In the data set [30], each time realization of 4097 values was divided into 23 parts of 178 values, which corresponded to 1 second. In [31], presented on the web platform Kaggle, using machine learning algorithms from [29], a classification of 1 second length records was carried out.

In this work, we also used the above mentionedtime realizations of brain activity with a length of 178 values. Fig. 2 shows the time realizations of EEG from the 1-st class (epileptic seizure) at the top and realizations from other classes at the bottom.

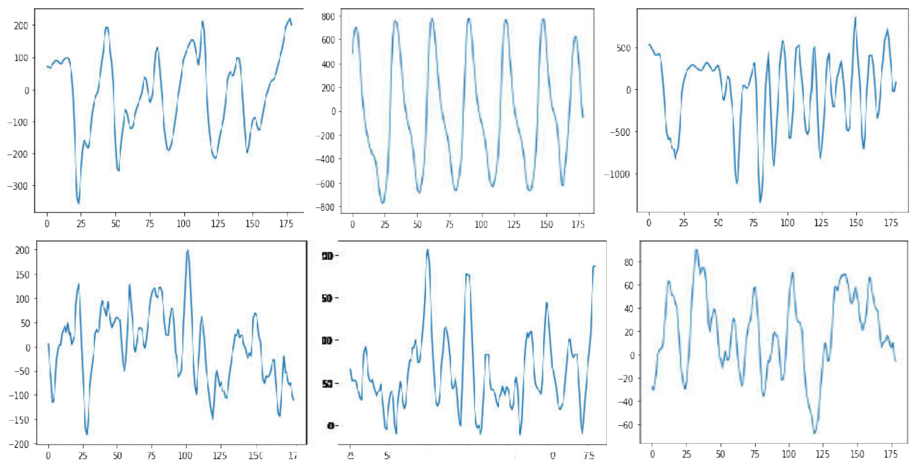

**Fig. 2.**Realizations of EEG of an epileptic seizure at the top and other classes at the bottom

Fig. 3 shows the recurrence plots corresponding to the time realizations shown in Fig. 2. It is worth noting that it is almost impossible to visually find differences between the EEG classes both in realizations and recurrence plots.

## 5 Neural networks for image classification

Currently, in connection with the increased computing power and the appearance of database images, computer vision technologies have become very common. It became possible to apply these technologies not only in various fields of scientific and technical activity but also in everyday life. The best results of image recognition have been shown by deep neural networks, in particular the convolutional neural network, which in contrast to the multilayer perceptron, are taken into account two-dimensional image topologies [32, 33].

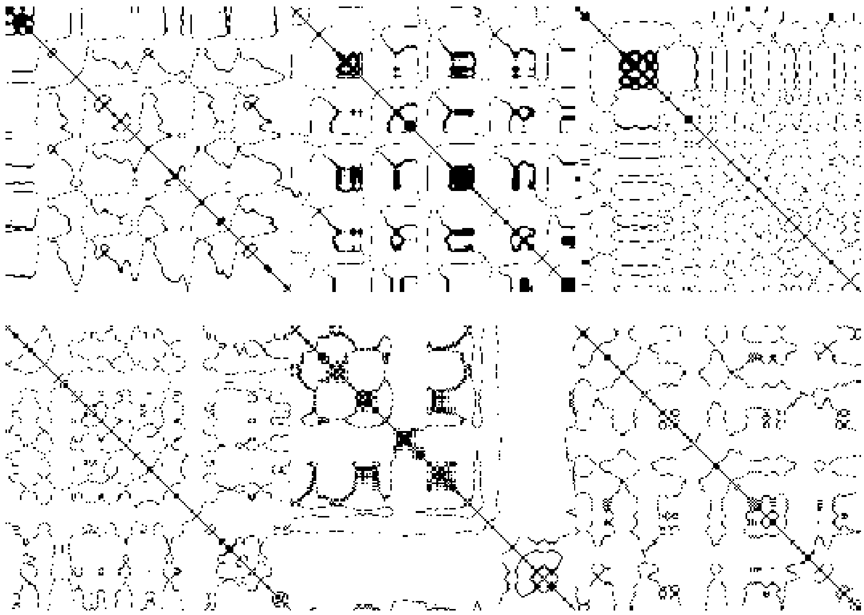

**Fig. 3.**Recurrence plots of an epileptic seizure at the top and other classes at the bottom

Convolutional neural networks receive features in an end-to-end multilayer manner. Studies have shown that with an increase in the number of layers, the recognition accuracy does not increase significantly: at first, the accuracy can grow a little, but the more we increase the depth of the network, the worse it starts to classify. This is due to the fact that the networks are trained by the method of backward propagation of errors, and as a result of differentiation according to the chain rule, the gradient attenuates for sufficiently deep layers.

To solve this problem, the structure of a residual neural network was developed [34]. The main feature of the residual network is that the classification result of the extended network will be no worse than the base one. The main idea is to replace the usual sequential layer connection with a shortcut connection.

Shortcut connections skip several layers and match identifiers. Their outputs are added to the grouped layers outputs. The main unit of the residual network consists of two layers with weightswhich are not necessarily convolutional, and a shortcutconnection that simply transmits a signal to the output. The structure diagram of the residual network is shown in Fig. 4.

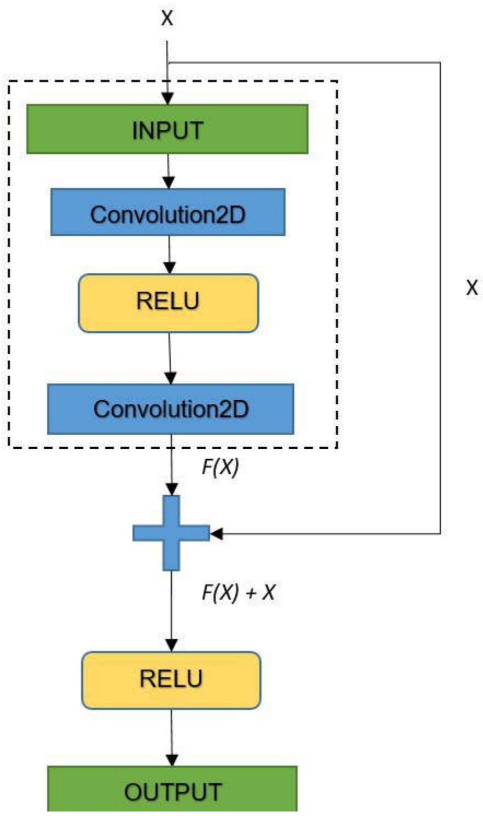


**Fig. 4.**Layout of the structure of the residual network

## 6 Experiment and Results

In the experiment, a residual neural network which had 131 layers with weights was used. The network consisted of 11 separate and 120 connected in blocks of a shortcut connection. The first 127 layers are intended for revealing characteristics (features), the last 4 used for constructing the classification function. The deep residual neural network contained ten blocks, three convolutional layers, and one fully connected layer. The output of the last fully connected layer is fed to the logistic function, which distributes into two classes. Neurons in a fully connected layer are connected to all neurons in the previous layer. Sub-sample layers follow after the second and third convolutional layers. The ReLU function is used to the output of each convolutional and fully connected layer. For training on the network, the adaptive learning rate optimization algorithm Adam was used.

The experimental data are taken from [31]. The dataset consists of 5 classes that contain records of the brain activity of different human conditions. The experiment was a binary classification of EEG realizations, where the epileptic seizure class was compared with the rest.

Each class consists of 100 files, where each file contains records about a single person. Each file contains records of brain activity for 23.5 seconds. Each time series contains 4097 values. So, respectively, the dataset contains records of brain activity about 500 individuals for 23.5 seconds, which consists of 4097 values. As a result, 11500 time series were obtained with a length of 178 values for 1 second interval.

The experiment was first conducted on a sample of 7500 realizations (6000 without a seizure / 1500 with a seizure), where 6000 (4800 without a seizure / 1200 with a seizure) were used for training and 1500 (1200 without a seizure / 300 with a seizure) for the test. Then, to determine the effect of sample size on the quality of classification, a whole dataset was used (11500 realizations), where 8500 realizations were chosen for training (6800 without a seizure / 1700 with a seizure) and 3000 for a test (2400 without a seizure / 600 with a seizure).

The classification results are presented in the confusion matrix (Table 1),where the symbol P means that the object was classified as belonging to a positive class (seizure), N means belonging negative class (withoutseizure), the symbol T shows that the class was determined correctly, and F shows incorrect determination.

**Table 1.**Confusion matrix

| | Seizure (True) | Withoutseizure (False) |
|---|---|---|
| Positive | 282(TP) | 6(FP) |
| Negative | 18(FN) | 1194(TN) |

Based on the confusion matrix, the classification evaluation metrics were calculated and they are presented in Table 2.

**Table 2.**Classification evaluation metrics

| | Seizure (True) |
|---|---|
| Accuracy | 0.984 |
| Precision | 0.9792 |
| Recall | 0.94 |
| F1 score | 0.9592 |

It is worth noting that the classification results obtained in the present work based on the method of recurrence plot visualization are not inferior in accuracy to the results obtained in [31] for several different classifiers.

## Conclusion

In the work, a fairly new approach to solving the task of time series classifying by the example of EEG realizations has been considered.The proposed approach, instead of extracting quantitative features of time series, has been based on the series transformation in the images and the further classification of the obtained images by deep neural networks. As conversion from time series to black and whiteimage, the construction of the recurrenceplothas been used.

Residual neural networkhas beenselected as an image classifier. Binary classification of EEG realizations, which contained records of an epileptic seizurehave beencarried out.The data for the experiment were records of brain activity of 178 values, which corresponds to 1 second. The binary classification resultwas the detection of an epileptic seizure. The results haveshown that the considered classification method has a fairly high classification accuracy even with a short length of EEG realizations. Indicators of classification quality the accuracy and F1-score were equal, respectively, 0.984 and 0.959.

The conducted experiment has confirmed the success of the approach to the time series classification by visualizing them. Further quality improvement may be possible in two ways. The first is to improve the architecture of the neural network, and the second is to develop methods for increasing the visual difference between recurrenceplots of different time series classes. In our future studies, we intend to focus on study and training the deep residual neural networks designed to recognize recurrence plots of time series from various datasets.

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