IT PARKINSON'S DISEASE DIAGNOSTICS BASED ON THE FREEZING OF GAIT ANALYSIS USING LONG SHORT TERM MEMORY NEURAL NETWORK

ULADZIMIR A. VISHNIAKOU, YIWEI XIA

Belarusian State University of Informatics and Radioelectronics (Minsk, Republic of Belarus)

Abstract. An analysis of methods for processing data from gait deceleration sensors for detecting Parkinson's disease and a description of the development of a Parkinson's recognition system based on neural networks with long short term memory (LSTM) are performed. The data used was a publicly available dataset of gait deceleration scores of patients with Parkinson's disease, obtained using three wearable sensors to collect data from different parts of the body. The research was carried out using machine learning using an LSTM neural network. First, the DAPHNet datasets were segmented using a fixed sliding window algorithm. The wavelet algorithm was then used to extract features from the data set: wavelet entropy and energy, wavelet waveform length, variance and standard deviation of wavelet coefficient. Next, a data enhancement algorithm was used to balance the number of samples in the data sets. To train the model, an LSTM neural network was built with a six-layer network structure: input layer, LSTM layer, reLU layer, fully connected layer, Softmax layer and output layer. After training the model for 1000 iterations, the LSTM neural network algorithm achieved 96.3 % accuracy, 96.05 % precision, 96.5 % sensitivity, and 96.24 % average F1 score for recognizing Parkinson's disease based on test datasets. Similar studies conducted by other scientific organizations achieved a maximum accuracy of 91.9 % for the same data sets.

Keywords: deep learning, acceleration sensor, time series data, long short term memory neural network, wavelet feature.

Conflict of interests. The authors declare no conflict of interests.

IT-ДИАГНОСТИКА БОЛЕЗНИ ПАРКИНСОНА, ОСНОВАННАЯ НА АНАЛИЗЕ ЗАМЕДЛЕНИЯ ДВИЖЕНИЙ ПАЦИЕНТА С ИСПОЛЬЗОВАНИЕМ LSTM НЕЙРОННОЙ СЕТИ

Ю. А. ВИШНЯКОВ, ИВЭЙ СЯ

Белорусский государственный университет информатики и радиоэлектроники
(г. Минск, Республика Беларусь)

Аннотация. Выполнены анализ методов обработки данных датчиков замедления походки для выявления болезни Паркинсона и описание разработки системы распознавания Паркинсона на основе нейронных сетей с долговременной кратковременной памятью (LSTM). Используемые данные представляли обще-

доступные наборы показателей замедления походки пациентов с болезнью Паркинсона, полученных с помощью трех носимых датчиков для сбора данных с различных частей тела. Исследования проводили посредством машинного обучения с применением нейронной сети LSTM. Сначала наборы данных DAPHNet сегментировали с помощью алгоритма фиксированного скользящего окна. Затем алгоритм вейвлета применяли для извлечения признаков из набора данных: энтропии и энергии вейвлета, длины формы вейвлет-сигнала, дисперсии и стандартного отклонения вейвлет-коэффициента. Далее алгоритм улучшения данных использовался для балансировки количества выборок в наборах данных. Для обучения модели была построена нейронная сеть LSTM с шестислойной сетевой структурой: входной слой, слой LSTM, слой reLU, полностью подключенный слой, слой Softmax и выходной слой. После обучения модели в течение 1000 итераций алгоритм нейронной сети LSTM достиг 96,3 % точности, 96,05 % прецизионности, 96,5 % чувствительности и 96,24 % среднего значения F1 для распознавания болезни Паркинсона на основе тестовых наборов данных. Аналогичные исследования, проведенные другими научными организациями, позволили достичь максимальной точности 91,9 % для тех же наборов данных.

Ключевые слова: глубокое обучение, датчик ускорения, данные временных рядов, нейронная сеть с длительной кратковременной памятью, вейвлет-функция.

Introduction

Parkinson's disease [1] is a chronic neurodegenerative disease in which patients may present with a variety of clinical manifestations including resting tremor, muscle tonus, and bradykinesia. Freezing of gait (FoG) is defined as a brief, sudden suspension or significant reduction in the patient's pace when attempting to walk or in the process of moving forward. It usually lasts for a few seconds, and occasionally for up to 30 s. In the most severe cases, FoG can occur at any time when the patient is walking, and is accompanied by a certain degree of leg tremors.

FoG [2] often occurs when starting, turning or passing through narrow aisles or doors, and is more likely to occur when patients are stressed. 81 % of patients develop FoG after 20 years of disease, and it becomes more frequent as the disease progresses. The patient's quality of life decreases dramatically. Therefore, one of the main goals of Parkinson's disease treatment is to recognize FoG behavior and then use medical treatment to improve patient condition with Parkinson's disease.

The new approach to human gait recognition is proposed, based on the quarterly deviation of the normal distribution to determine the state of human movement and on a Bayesian model with binomial distribution to identify signs and select the best ones [3]. To realize FoG detection with high performance [4] the methods to build FoG detection models using deep convolutional and recurrent networks were proposed. These alarming figures make Parkinson's disease an important focus of attention. In [5] presented contributions that suggest wavelet techniques as a useful tool to perform a gait and arm swing analysis; this represents an important approximation that can contribute to describe and differentiate people with Parkinson's disease in early stages of the disease. In [6] authors proposed a novel intelligent Parkinson detection system based on deep learning techniques to analyze gait information. In [7] presented continuous monitoring activity of daily living (ADLs) and classification freezing of gait episodes using Wi-Fi and radar imaging. The objective of [8] was to test the success of the data set obtained by a wearable health assistant developed for the symptom of freezing in gait of Parkinson's patients and to increase the success of the system. In [9] aimed to identify trends, challenges and opportunities in the development of FoG detection and prediction systems. Inspired by state-of-art deep learning techniques [10] aimed to improve the detection model by proposing a feature learning deep denoising auto encoder to learn the salient characteristics of Parkinsonian gait data that is applicable to different walking styles for the elimination of manually handcrafted features. The proposed model achieved a generalization accuracy of 89.2 % and a geometric mean of 88.8 % [11]. The growing popularity and success of Transformer networks in natural language processing and image recognition motivated the authors to develop a novel method for the problem based on an automatic features extraction via Transformers. The use of Transformers in 1D signal is not really widespread yet, but in [12] shown that they are effective in extracting relevant features from 1D signals. This work used the LSTM neural network algorithm to recognize the FoG in Parkinson's disease.

Methodology

In this paper, the model is trained and tested on the DAPHNet datasets. The issue of gait freezing in Parkinson's disease was studied in a study by [13]. The dataset was recorded in the lab with emphasis on generating many freeze events. Users performed three kinds of tasks: straight line walking, walking with numerous turns, and finally a more realistic ADL task, where users went into different rooms while fetching coffee, opening doors, etc. The dataset comprises 3 wearable wireless acceleration sensors – recording 3D acceleration at 64 Hz. The sensors are placed at the ankle (shank), on the thigh just above the knee, and on the hip. The Fig. 1 shows the position of the sensor on the experimenter.
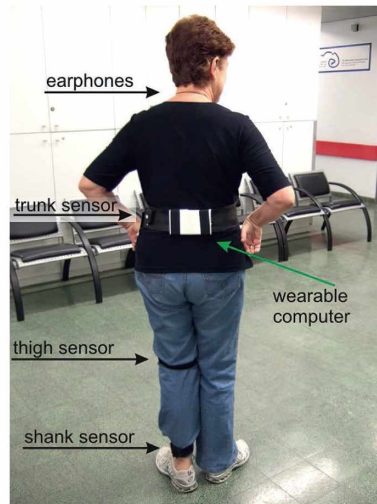

Fig. 1. The position of the sensor on the experimenter

These datasets are multivariate time series datasets. There many records in total, each records contains 1 time stamp, 9 acceleration (each sensor has x, y, z axis acceleration) and 1 label. The data used in this work has a total of 1 917 887 data records, but it only contains 237 FoG events. The FoG duration is very short, so the number of FoG records is far less than the number of non-FoG records in the datasets, so the datasets have a serious data imbalance problem. There are two ways to deal with the data imbalance, the one is to overcome the imbalance of sample size at the sample level, for example, to reduce or increase the sample size of one type in the classification by oversampling and under sampling, so as to achieve the sample balance. The another one is to overcome the imbalance of sample size at the level of model algorithm, such as assigning higher weights to a few classes by using the class weights parameter. In this work, the new approach was to first extract features from the original dataset and then randomly reduce the number of non-FoG feature data samples to achieve a 1:1 ratio between the number of feature data of the two classes in the dataset.

The original data is a continuous stream of time series data, so the features cannot be extracted directly and the data needs to be segmented. In the current research work, action data segmentation algorithm generally uses a sliding window with fixed window size. In this work, window length is 32, the overlap coverage is 50 %, and the window period is 0.5 s. Since the FoG signal is a non-stationary signal, the relevant statistical features, such as maximum, minimum and average, are directly extracted, which do not show the actual characteristics of the FoG signal. However, the transformation of the FoG signal is slow and can be considered as short-time smooth, which means it is smooth in a short period of time (20–30 ms), so it is more appropriate to use the wavelet transform method to extract the features of the signal.

The method used for this experiment is to decompose four layers of wavelet coefficients using db6 wavelet, and then calculate the statistical features of each layer of wavelet coefficients. Five wavelet features are extracted from each layer of wavelet coefficients, and they are wavelet entropy, wavelet energy, wavelet waveform length, wavelet coefficient variance, and wavelet coefficient standard deviation. There are three axes on each sensor, so there are 75 wavelet features in total.

Long short term memory (LSTM) network [14] is a modified recurrent neural network, mainly by introducing a gating mechanism to control the accumulation rate of information, including selec-

tively adding new information and selectively forgetting previously accumulated information, thus improving the long-range dependency problem of recurrent neural networks (RNNs) and alleviating the gradient disappearance problem during the training of long sequences. The idea of LSTM is that the hidden layer of the original RNNs has only one state, which cannot handle long-range data. So the LSTM adds a storage unit to store the long-term state, called cell state. Finally, a gate unit is added to control the input, output or forgetting of information. The Fig. 2 shows the structure of LSTM neural networks.
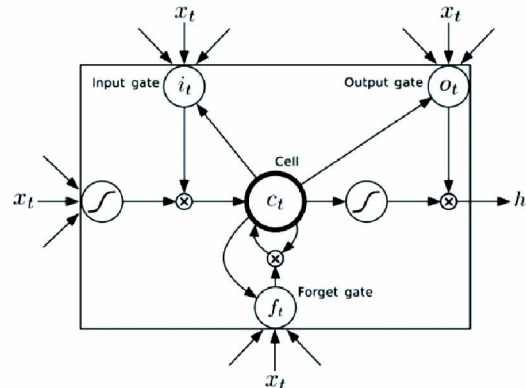

Fig. 2. The structure of long short-term memory neural networks

Three gates are placed in a cell, called the input gate, the forget gate and the output gate. A message enters the LSTM network and can be judged as useful or not according to the rules. Only information that meets the algorithm's certification is left behind, while information that does not meet the criteria is forgotten through the forgetting gate. The function of the three LSTM gates:

1) forgetting gate: determines how much information needs to be forgotten in the previous moment's memory cell state and how much information is retained in the current memory cell state;

2) input gate controls information which should be added to the current memory cell state;

3) output gate controls information from the current memory cell state should be output.

This work is conducted under the widows 11 platform, with MATLAB R2022b software under i7-10750H CPU. MATLAB is a combination of the word's matrix laboratory, which is a high-tech computing environment for scientific computing, visualization and interactive programming. It integrates many powerful functions such as numerical analysis, matrix computation, visualization of scientific data, and modeling and simulation of nonlinear dynamic systems in an easy-to-use window environment, providing a comprehensive solution for scientific research, engineering design, and many scientific fields where effective numerical computation must be performed, and largely free from the editing mode of traditional non-interactive programming languages. The following are the main MATLAB toolboxes that are used in the work.

1. Classification learner toolbox. This toolbox is integrated with machine learning algorithms, we use the machine learning algorithms contained in it to do experiments to compare the effect of LSTM algorithm.

2. Deep network designer toolbox. This toolbox provides a visual way to build a network model, we use this toolbox to build LSTM neural network model.

Experiments and results

Since the data in the publicly available DAPHNet dataset was labeled, the experiments conducted in this work were limited to studying the results of binary classification. The steps of this experiment were as follows.

1. The data were cleaned and the abnormal data and missing data were removed.

2. Executed segmenting the data through a time window of size 32, with an overlap of 50 %.

3. Executed extracting features from the data in each window. The authors used db6 wavelet to decompose four layers of wavelet coefficients, and then calculated the statistical features of each layer of wavelet coefficients. Five wavelet features were extracted from each layer of wavelet coefficients: wavelet entropy, wavelet energy, wavelet waveform length, wavelet coefficient variance and wavelet coefficient standard deviation. There are three axes on each sensor, so there are 75 wavelet features in total.

4. The data augmentation method was used to equalize the amount of data in both categories in the datasets.

5. The feature datasets were divided into training datasets and testing datasets according to 9:1.

6. The training datasets were inputted into the LSTM model for 1000 epochs to optimize the LSTM model, and the fivefold cross-validation method was used.

7. The recognition accuracy of the LSTM model was tested on the testing datasets.

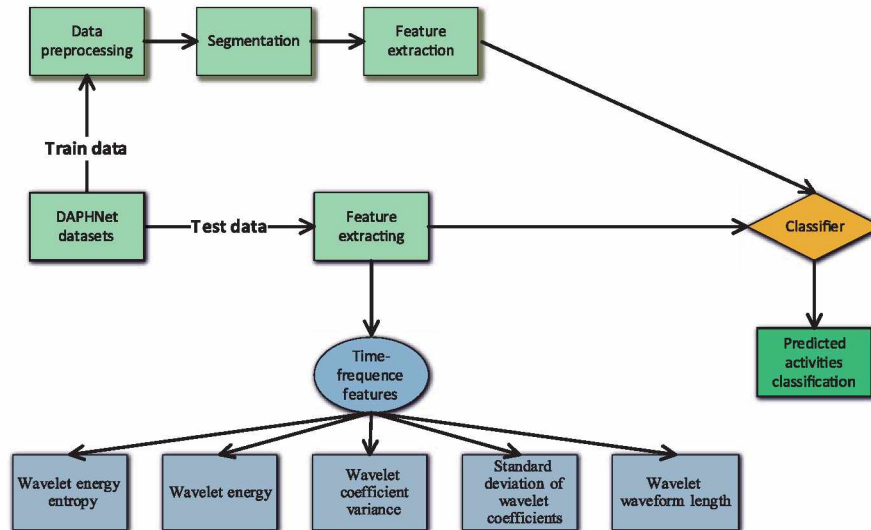The Fig. 3 illustrates the process of training and testing the dataset in this experiment.

Fig. 3. The process of training and testing the dataset in this experiment

The LSTM neural network in this work had a total of six layers and 1.9K learnable properties. The Fig. 4 illustrates the structure of the LSTM neural network.

	Name	Type	Activations	Learnable Properties	States
1	sequenceinput Sequence input with 75 dimensions	Sequence Input	75(C) × 1(B) × 1(T)	–	–
2	lstm LSTM with 6 hidden units	LSTM	6(C) × 1(B)	InputWeights 24 × 75 RecurrentWeights 24 × 6 Bias 24 × 1	HiddenState 6 × 1 CellState 6 × 1
3	relu ReLU	ReLU	6(C) × 1(B)	–	–
4	fc 2 fully connected layer	Fully Connected	2(C) × 1(B)	Weights 2 × 6 Bias 2 × 1	–
5	softmax softmax	Softmax	2(C) × 1(B)	–	–
6	classoutput crossentropyex with classes '1' and '2'	Classification Output	2(C) × 1(B)	–	–

Fig. 4. The structure of long short term memory neural networks

The Tab. 1 showes the LSTM neural network model hyperparameter setting table in this experiment. The Fig. 5 showed the process of training the LSTM model in 1000 epochs.

Table 1. Long short term memory neural network model hyperparameter setting table in this experiment

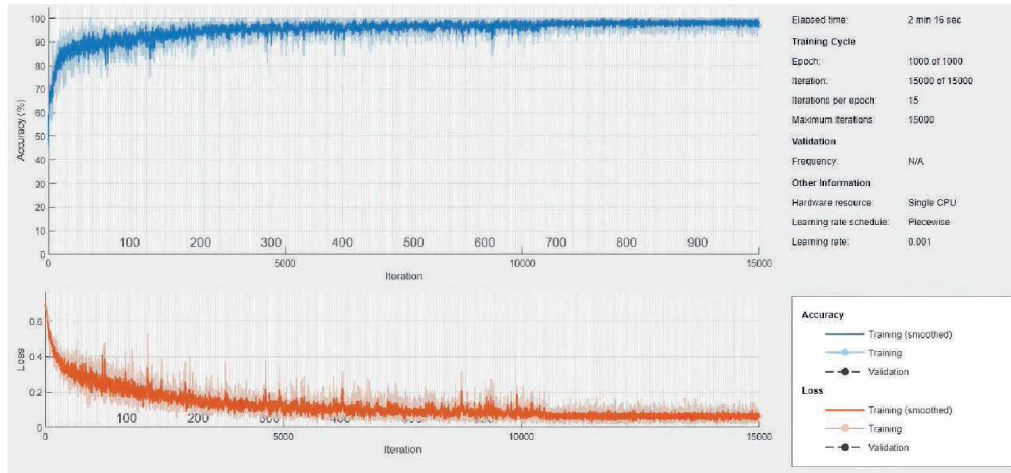| Number	Parameter name	Parameter value
1	MiniBatchSize	64
2	MaxEpochs	1000
3	InitialLearnRate	0.01
4	LearnRateDropFactor	0.10
5	LearnRateDropPeriod	700
6	Shuffle	Every-epoch
7	Optimization	Adam

Fig. 5. The process of training the long short-term memory model in 1000 epochs

As can be seen in Fig. 5, after entering training datasets into the model and completing 1000 training periods, the LSTM model converged (losses assumed the same value). The Fig. 6 showed comparison of prediction results for the training and testing datasets. The accuracy of the LSTM model was 96.29 % for the testing datasets and 97.13 % for the training datasets. The accuracy of the testing datasets were lower than the accuracy of the training datasets by 0.84 %, which meant that the model was not over fitted. The Fig. 7 shows confusion matrix of training and testing datasets.
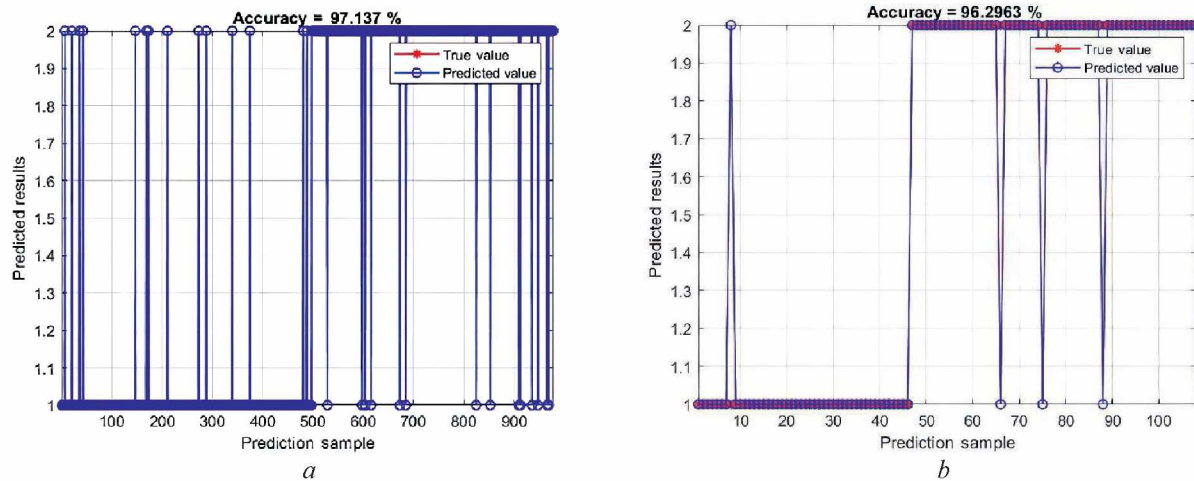

Fig. 6. Comparison of forecasting results for data sets: *a* – training; *b* – test
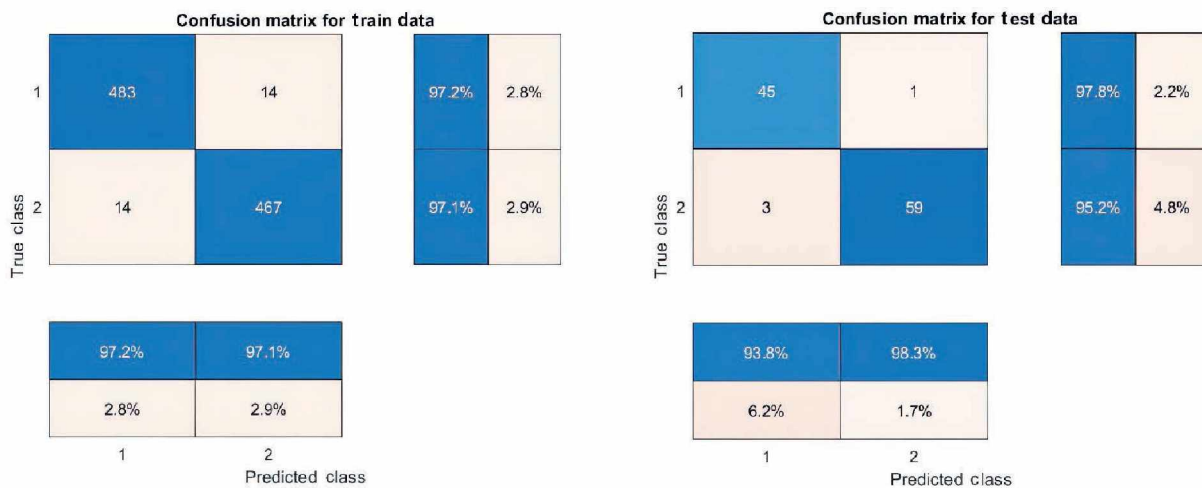

Fig. 7. Confusion matrix of data sets: *a* – training; *b* – test

The categories were distributed equally in the training and testing datasets, as it can be seen in Fig. 7. The confusion matrix was used to calculate various performance metrics for the classification problem, including sensitivity, accuracy and F1 score for a particular category. The Tab. 2 shows the experimental results of Parkinson's disease recognition based on test datasets using LSTM.

Table 2. The experimental results of Parkinson's disease recognition based on test datasets using long short term memory

Dataset	Average precision, %	Average sensitivity, %	Average F1 score, %	Test accuracy, %
DAPHNet	96.05	96.50	96.24	96.30

In summary, the accuracy of the LSTM-based Parkinson's disease model could reach 96.3 % on the test dataset and 97.13 % on the training dataset. On the testing datasets, the average accuracy was 96.05 %, the average sensitivity was 96.50 %, and the average F1 score was 96.24 %. This experimental result showed that the recognition of Parkinson's disease using LSTM algorithm based on FoG data was effective. The test accuracy of this study and existing studies on the same datasets are compared in the Tab. 3.

Table 3. Compare with others' research

Dataset	Researcher	Research methods	Test accuracy, %
DAPHNet	[15]	Deep convolutional neural networks with five-layer CNN	80.7
DAPHNet	[16]	LSTM based on the unprocessed datasets	83.4
DAPHNet	[17]	Improved DL neural networks model	91.9
DAPHNet	[16]	SVM	79.5
DAPHNet	The proposed	LSTM based on the wavelet features datasets	96.3

The Tab. 3 shows that the LSTM based on the wavelet features datasets had the highest test accuracy with 96.3 % for the same datasets.

Conclusion

1. The article presents the state of the art of the most relevant freezing of gait recognition systems in Parkinson's disease and discusses their results. Using the sliding fixed window algorithm, data segmentation was applied to the public dataset, and then from the windowed data, we extracted five types of wavelet features: wavelet entropy, wavelet energy, wavelet waveform length, wavelet coefficient variance and wavelet coefficient standard deviation. The data Augmentation algorithm was used to balance the number of classes in the extracted feature datasets. Datasets of objects were used in long short term memory neural network model, and the model had a six-layer network structure.

2. Based on the DAPHNet datasets of patients for IT diagnostics of Parkinson's disease, the recognition accuracy for the long short term memory algorithm reached 96.3 %. Our results of IT diagnostics of Parkinson's disease were compared with the known results of other researchers, the best of which are 91.9 %.

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Authors' contribution

The authors contributed equally to the writing of the article.

Information about the authors

Vishniakou U. A., Dr. of Sci. (Tech.), Professor at the Department of Infocommunication Technologies, Belarusian State University of Informatics and Radioelectronics (BSUIR)

YiWey Xia, Postgraduate at the Department of Infocommunication Technologies, BSUIR

Address for correspondence

220013, Republic of Belarus,
Minsk, P. Brovki St., 6
Belarusian State University
of Informatics and Radioelectronics
Tel.: +375 44 486-71-82
E-mail: vish@bsuir.by
Vishniakou Uladzimir Anatol'evich