Conference materials
UDC 064.89.032.26
DOI: https://doi.org/10.18721/JPM.153.209

# Testing the layout of the rail condition monitoring system using LSTM recurrent neural networks

M. A. Denisenko [1], A. S. Isaeva [1] ✉, I. N. Kots [1]

[1] Southern Federal University, Taganrog, Russia

✉ isaevaas@sfedu.ru

**Abstract.** In this paper the solution of the multiclass classification problem of the events recognition during the movement of a bogie model along rails containing defects is described. Testing the layout of the rail condition monitoring system was described. The problem was solved using LSTM recurrent neural networks and implemented by Python programming language. The neural network was trained to classify three type of events used acceleration data. The method of the data collection and the description of the test stand is given. Conclusions about the efficiency of event recognition from a given set are made.

**Keywords:** rail defect monitoring, neural network, multiclass classification problem

**Funding:** The work was carried out at the expense of funds, task No. FENW-2020-0022 for the implementation of scientific research carrying out scientific research at the expense of the Federal budget, in terms of scientific activities on the topic "Development and research of methods and means of monitoring, diagnostics and forecasting state of engineering objects based on artificial intelligence".

**Citation:** Isaeva A. S., Denisenko M. A., Kots I. N., Testing the layout of the rail condition monitoring system using LSTM recurrent neural networks, St. Petersburg State Polytechnical University Journal. Physics and Mathematics. 15 (3.2) (2022) 51–55. DOI: https://doi.org/10.18721/JPM.153.209



Материалы конференции
УДК 064.89.032.26
DOI: https://doi.org/10.18721/JPM.153.209

# Тестирование прототипа системы мониторинга состояния рельсового пути с использованием LSTM рекуррентных нейронных сетей

М.А. Денисенко [1], А.С. Исаева [1] ✉, И.Н. Коц [1]

[1] Южный федеральный университет, г. Таганрог, Россия

✉ isaevaas@sfedu.ru

**Аннотация.** В статье описано решение задачи многоклассовой классификации событий при движении модели тележки по рельсам, содержащим дефекты. Задача была решена с использованием рекуррентных нейронных сетей LSTM и реализована на языке программирования Python. Дана методика сбора данных и описание испытательного стенда. Сделаны выводы об эффективности распознавания событий из заданного набора.

**Ключевые слова:** мониторинг дефектов рельсового пути, нейронные сети, многоклассовая классификация

**Финансирование:** Научные исследования выполнены за счет средств федерального бюджета, в рамках научной деятельности по теме «Разработка и исследование методов и средств мониторинга, диагностики и прогнозирования состояния инженерных объектов на основе искусственного интеллекта» (задание № FENW-2020-0022).

**Ссылка при цитировании:** Исаева А. С., Денисенко М. А., Коц И. Н. Тестирование прототипа системы мониторинга состояния рельсового пути с использованием LSTM рекуррентных нейронных сетей // Научно-технические ведомости СПбГПУ. Физико-математические науки. 2022. Т. 15. № 3.2. С. 51–55. DOI: https://doi.org/10.18721/JPM.153.209



## Introduction

Improving the efficiency of detecting defects in the railway track is an urgent task for any state that implements railway communication on its territory. The large length of railway tracks (more than 85 thousand kilometers of general-purpose tracks in the Russian Federation) makes it difficult to regularly inspect them and detect defects. All over the world, systems for diagnosing the condition of railway tracks are being actively developed, including the use of artificial intelligence systems [1–3]. Development of monitoring systems installed on existing railway cars and (or) trains, transfer and aggregation of the received data, analysis and identification of places of possible defects sems to be a good strategy. Data from a microphone, an accelerometer, a gyroscope, a photos of a railway tracks, etc. could be analyzed. In this paper we used information about accelerations that a vehicle moving on rails is subjected to.

## Materials and Methods

A model of a railway bogie was designed and manufactured for this experiment. Bogie is complected with an NVIDIA Jetson module, a Bluetooth/WiFi wireless data transmission module, sensitive elements - an inertial accelerometer module, and a power bank. Figure 1 shows 3D model of a railway bogie and a railway bogie with installed components.

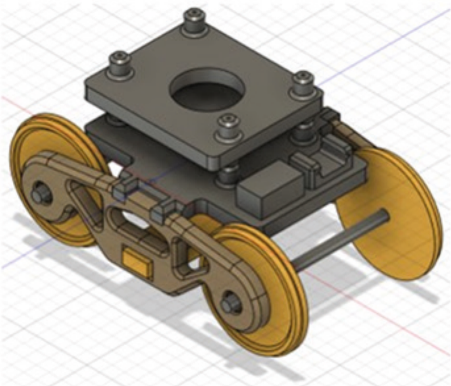
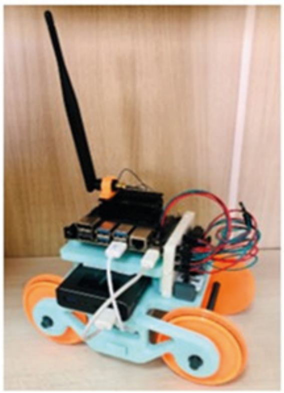

Fig. 1. 3D model of a railway bogie and a railway bogie with installed components

The rail track model consists of two metal L-shaped (3 × 3 cm) profiles 4 mm thick and 2 m long, fixed on wooden bars. The bogie rolls along the top edge of the profile. There are two such structures, so we have a total track length of 4 m and a joint that imitates a non-welded butt rail joint. The model was leveled and fixed on a solid base. A defect imitating rail spalling was applied to the working surface.

For the task of multiclass classification solving six variables were used: activity, user, timestamp, x-axis, y-axis, z-axis. Activity is the target variable and its takes three values: 1 (corresponds to the event "driving on rails"), 2 (corresponds to the event "non-welded joint of the rail track detected") and 3 (corresponds to the event "defect detected "). The x-axis, y-axis, z-axis are accelerations along the x, y, z axes. Numeric variables were normalized and converted to binary features, i.e., to a unitary code (one-hot encoding). In total, the training sample included 1957111 acceleration measurements, the test sample included 489275 measurements, that is, 80% and 20%, respectively, of the entire data set: 840,536 acceleration measurements were collected when a bogie model traveled on rails that did not contain defects, 775,118 acceleration measurements when a bogie model traveled along a joint, and 830,735 acceleration measurements when a bogie model traveled along a defect. Accelerations were taken at a sampling rate of 400 Hz.

In this case, since the data was collected for a specific task, the features are not sparse and the model does not contain redundant features for which it would be necessary to apply selection algorithms.

Figure 2 shows acceleration versus time graphs for tree possible events: "driving on rails", "defect detected " and "non-welded joint of the rail track detected".

The sensor on railway bogie model is oriented as follows: the x-axis coincides with the direction of the bogie movement along the rails, the y-axis is perpendicular to the x-axis in the horizontal plane, and the z-axis is co-directed with the gravitational acceleration g.

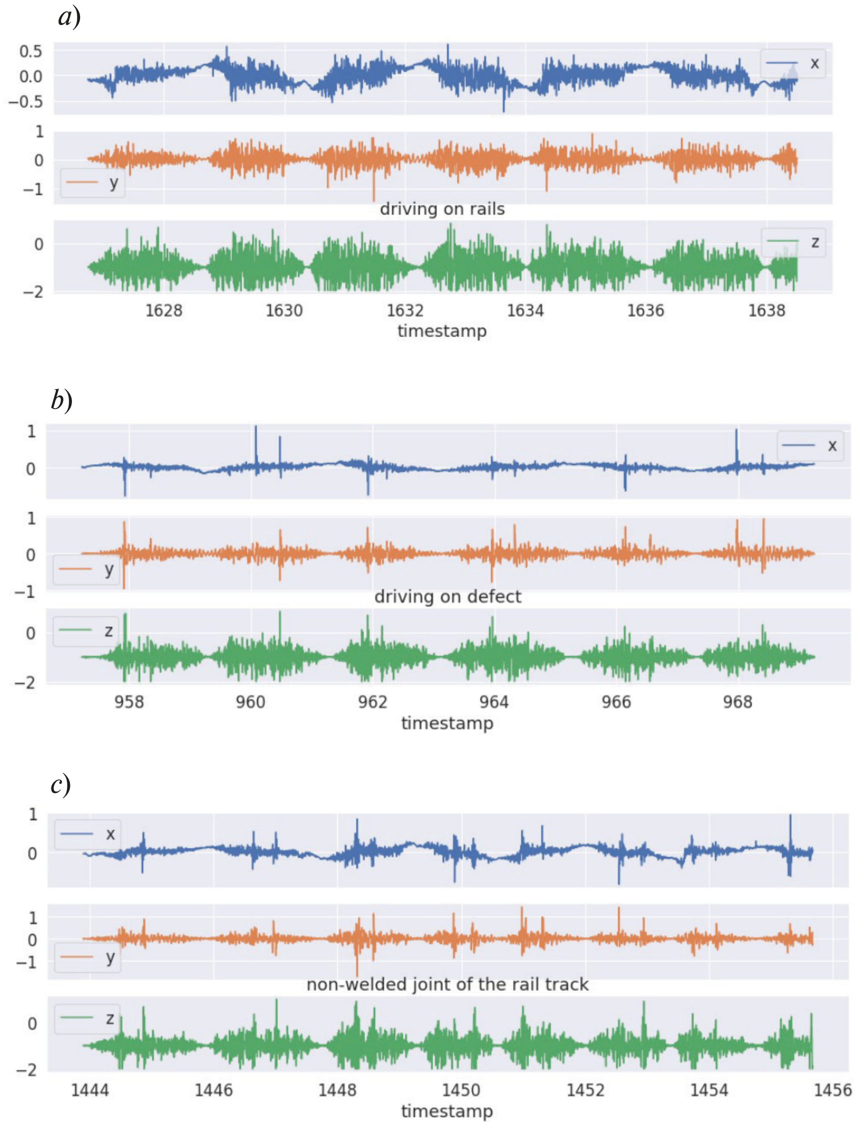


Fig. 2. Acceleration data: x-axis, y-axis and z-axis curves for "driving on rails" event (*a*), for "defect detected " event (*b*) and for "non-welded joint of the rail track detected" event (*c*)

Graphs in Figure 2 are built on 4000 values of the timestamp variable. Timestamp variable counts every 0.0025 second of the experiment, so it is slightly modified time scale. It can be seen from the graphs that 6-7 full round-trip cycles of the bogie movement fit into this time interval. This is important to note, since the entire set of data must be divided into frames for training the neural network, and we did it in such a way that each frame must include at least one full cycle of movement. During the training of the neural network, frames of 200 and 500 values of the timestamp variable were used.

To implement the event recognition algorithm, a network of long short-term memory (LSTM) was used. It is a one of recurrent neural networks. The LSTM network is well adapted to learning on the problems of classification, processing and forecasting of time series in cases where important events are separated by time lags with indefinite duration and boundaries. To improve the performance of the model, a bidirectional LSTM network (Bidirectional LSTM) was used.

Unlike a conventional LSTM network, a bidirectional LSTM network is trained on both the direct and external side of the input data [4].

The LSTM neural network was implemented using the Keras library. It consists of one layer of 164 neurons. The model was trained for 20 epochs, batch size = 32.

### Results and Discussion

The neural network determines the event with an accuracy of 93%. The largest number of errors occurs when defining "defect detected" event. The confusion matrix of the developed model is shown on Figure 3.

Despite a convolutional neural network (CNN) it is the most commonly used architecture for this type of problem [5], we have obtained good result with LSTM neural network. We suppose that data, collected not in the laboratory, but through a real railway bogie driving, would reduce the accuracy.

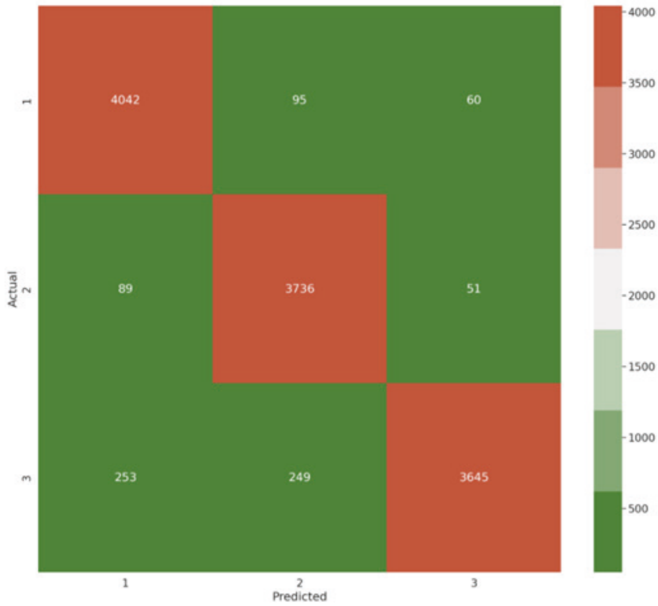


Fig. 3. Confusion matrix of the developed model

### Conclusion

The solution of the multiclass classification problem of the events recognition during the movement of a bogie model along rails containing defects and training of the LSTM recurrent neural networks is described in this paper. We obtained 93% accuracy of the events recognition.

### REFERENCES

1. **Giben X., Patel V. M., Chellappa R.,** Material classification and semantic segmentation of railway track images with deep convolutional neural networks IEEE International Conference on Image Processing (ICIP). 2015. Pp. 621–625.

2. **Gibert X., Vishal P., Chellappa R.,** Robust Fastener Detection for Autonomous Visual Railway Track Inspection 2015 IEEE Winter Conference on Applications of Computer Vision. 2015. Pp. 694–701.

3 **Yang C., Sun Y., Ladubec C., Liu Y.,** Developing Machine Learning-Based Models for Railway Inspection Applied Sciences. 2021. Vol. 11 (1) 13.

4. **Staudemeyer Ralf C., Morris Eric R.,** Understanding LSTM - a tutorial into Long Short-Term Memory Recurrent Neural Networks ArXiv. 2019

5. **Fawaz H., Forestier G., Weber J., Idoumghar L., Muller P. A.,** Deep learning for time series classification: a review. Data Mining and Knowledge Discovery. 2019. Vol. 33. No. 4. Pp. 917–963.

## THE AUTHORS

**DENISENKO Mark A.**
dema@sfedu.ru
ORCID: 0000-0001-5044-7482

**ISAEVA Alina S.**
isaevaas@sfedu.ru
ORCID: 0000-0002-5145-0963

**KOTS Ivan N.**
inkots@sfedu.ru
ORCID: 0000-0002-1257-7304

*Received 17.08.2022. Approved after reviewing 31.08.2022. Accepted 01.09.2022.*