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Neural network application to road surface type identification

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Road condition monitoring is an essential goal for transport infrastructure. It is important for the fast and safe evolution of autonomous vehicles, useful for advanced driver assistance systems and efficient road repair. In this paper we propose a solution to the problem of identifying the type of pavement using machine learning methods. Asphalt road, gravel road and cobbled road were the types of pavement quality, which were identified. The research community uses various types of sensors and data to solve this classification problem. This paper evaluates pavement type identification using data received from the inertial measurement unit installed in a vehicle and, in particular, data generated by the accelerometers. One car was used. The traffic route was chosen so that all three types of road surface were located on a small section of the road. The obtained data was used in training the long short-term memory recurrent neural network. The achieved accuracy of identification the type of road surface was 88.2 %.

Keywords: LSTM recurrent neural networks, inertial measurement unit, identification of the type of road surface.

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Introduction

Much attention has recently been paid to the development of methods and algorithms of the detection of road anomalies (such as speed bumps and potholes) and types of pavement. These developments can be used to improve the driving plan of autonomous vehicles, such as, slowing down before a known bumps or entering a paved or gravel road. It is essential to extend the life of an autonomous vehicle and improve passenger comfort. Road anomalies can be used as a guide for more accurate vehicle localization. Also, such techniques can help reduce the time to detect road anomalies and make city services more effective. A variety of sensors and systems are used to collect data: simple cameras, thermal infrared cameras [1], 3D laser scanning of the road surface [2], data from accelerometers and gyroscopes [3–6]. Automated algorithms for identifying road anomalies and road types are divided into three types: visual, vibrational, and based on 3D reconstruction [7]. Each of the above methods for obtaining data on the state of the road surface has its pros and cons: for example, the camera can only be used during daylight hours on a pavement without rain and snow, the stream of high-quality video and photo images is demanding on the bandwidth of the interfaces and memory, laser scanning does not allow real-time data processing, and so on. The work [7] is devoted to a detailed analysis of the most common methods, their advantages and disadvantages. The most widely used machine learning algorithms that applied by researchers to solve the problem of detecting road anomalies and identifying road types are convolutional neural networks and long short-term memory (LSTM) recurrent neural networks. There are well-known algorithms for representing a one-dimensional signal in a spectral matrix or encoded image, such as short-time Fourier transform, wavelet transform or transformation using gramian angular field. Thus, researchers applying the vibrational road surface recognition algorithm often use convolutional neural networks and deep convolutional neural networks. Using the LSTM recurrent neural network allows to work with accelerometer and gyroscope signals without converting them into an image.

Harishankar et al. [8] proposed a technique to clarify the location of a car by lanes, which allows levelling the low resolution of GPS measurements available in modern smartphones and making navigation systems more correct. Using the developed LaNet network based on LSTM, the authors teach it to remember a unique sequence of inertial data on sections of the roadway of the order of 100 m (90 % classification accuracy) and 200 m (100 % classification accuracy) and determine the lane corresponding to a particular set of inertial data. In contrast to [8], in this work we used frames corresponding to a smaller section of the path (about 10 m of road surface) and the neural network learned to determine not unique sequences of events, but patterns of inertial data corresponding to one or another type of road surface. Although in this work the route of the car is specified, the network can be used to analyze data from other road sections, provided that the data format is the same. Martinelli et al. [9] proposed a method for classifying pavement damage based on the analysis of vehicle accelerometer data. Short-time Fourier transform is used, and significant features, such as the coefficient of variation and the entropy computed from the energy of signal segments, are exploited to distinguish between well-localized pavement distresses caused by potholes and manhole covers and spread distress due to fatigue cracking and rutting. Three classes were distinguished: areas with large single defects such as potholes, areas with spread distress and defect-free areas. The frames corresponded to approximately 100 m of the road, the data were taken at a sampling rate of 100 Hz. The calculated matrices were analyzed using three artificial intelligence algorithms: support vector machine (SVM), decision tree (DT) and k-nearest neighbours (kNN). The maximum achieved recognition efficiency was 90.9 % for the decision tree, 91.9 % for the support vector machine and 90.9 % for the k-nearest neighbours method, which is comparable to the maximum accuracy of 88.2 % achieved in this work, with significantly smaller frame sizes and the absence of computational and time costs to perform a windowed Fourier transform. Basavaraju et al. [10] classified road surface damage based on the analysis of data from a 3-axis accelerometer and GPS sensor in the Apple iPhone 6 smartphone. The authors used three different cars as data collection vehicles to take into consideration the differences in the suspension quality of various types of cars. The camera was used to further manually label the data into three classes: containing large single defects such as potholes, containing cracks and defect-free areas. The dataset was divided into frames corresponding to 10 seconds of driving, the accelerometer sampling rate was 100 Hz, and the GPS sensor sampling rate was 1 Hz. The maximum achieved recognition efficiency was 90.15 % for the support vector machine, 88.35 % for the decision tree, and 92.12 % for a neural network containing 7 hidden neural layers. Note that in this work, a single-layer neural network is used and we used only one car.

Yao et al. [11] proposed a complex DeepSense neural network that combines a CNN and a recurrent network for the classification of three types of pavements: defect-free asphalt road (smooth type), asphalt road with defects (bumpy type) and gravel road (rough type). Authors of [11] compared the performance of DeepSense with algorithms such as random forest, SVM, neural networks and convolutional neural networks. The efficiency was: 63.89 % for random forest, 69.44 % for SVM, 72.92 % for convolutional neural network, 76.39 % for neural network and 84.81 % for DeepSense. The DeepSense is open source with open dataset, so we trained LSTM recurrent neural network on this dataset. It should be noted that dataset is really small (42 599 timestep variable values). LSTM recurrent neural network described in the paper showed an efficiency of 74.76 % on these data, which is slightly inferior to the results achieved by the authors for a convolutional neural network.

Materials and methods

In this work identification of the road type belongs to the type of multiclass classification problems. The target variable corresponds to road type and takes three values: 1 (cobbled road), 2 (gravel road) and 3 (asphalt road).

All the used data were obtained while driving one Volkswagen Polo. In this work the inertial measuring unit (IMU), which is part of the control and diagnostic unit of the automated system for monitoring and diagnosing the state of engineering objects, developed at the Design Center of the microelectronic component base of Artificial Intelligence Systems of the Southern Federal University, was placed in the car. IMU is a standard solution based on LIS331DLH (three-axis accelerometer), I3G4250D (three-axis gyroscope), LIS3MDL (three-axis magnetometer/compass), LPS25HB (barometer) chips. Only the accelerometer functionality was used in the experiment. The technical specifications of the LIS331DLH three-axis accelerometer are shown in Table 1.

The monitoring unit is oriented in the car as follows: the x-axis coincides with the direction of the car's movement, the y-axis is perpendicular to the x-axis in the horizontal plane, the z-axis is co-directed with the acceleration of gravity g. In addition to three axis accelerations at a 400 Hz sampling rate, the monitoring unit generates a large amount of data, from which, in this experiment, information on latitude and longitude was also used for developing the sorting algorithm. For tracking movements, a GPS/GLONASS module based on the GNSS (global navigation satellite system) module chip Neoway G7 was used. Technical specifications of the module are shown in Table 2.

A route, which includes three types of road surface: asphalt, gravel and paving stones, was chosen in the city of Taganrog, Rostov region. A map of the route with marked sections of various road surfaces and photos of road sections with different type of road surface is shown in Fig. 1. The car drove once over the entire route and then five more times along

T a b l e 1. Technical specifications of the sensor used in the data collection: LIS331DLH three-axis accelerometer.

Parameter	Measurement unit	Value
Standard full range	g	±2
Sensitivity	mg/digit	0.9–1.1
Sensitivity change vs temperature	%/°C	±0.01
Typical zero-g level offset accuracy	mg	±20
Bandwidth	Hz	400

T a b l e 2. Technical specifications of the sensor used in the data collection: Neoway G7

Parameter	Measurement unit	Value
GPS operating frequency	MHz	1575.42
Accuracy (open air)	m	Horizontal < 3; Vertical < 4.5
Sensitivity	dBm	−147
Baud rate	bps	9600

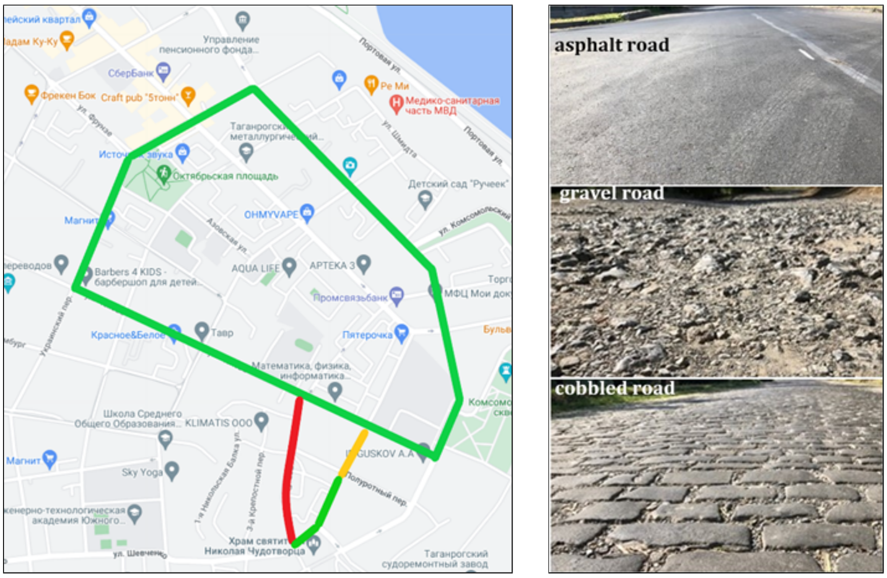

Fig. 1. Map with route (green areas indicate an asphalt road, red areas indicate a gravel road and yellow areas indicate a cobbled road)

a small section of the route in order to collect more data on driving on cobbled road and gravel road, which are small on length.

The dataset was divided into data obtained on three different types of pavements by filtering the data by geographic coordinates. The data was labelled automatically, which allows to quickly increase the size of the dataset if necessary. This resulted in a slight loss of data (data from the two asphalt pavement sections between the paved and unpaved sections has been lost), but allowed to sort data quickly and efficiently. To validate the sorting method, the data were mapped according to their belonging to a particular type of road pavement. The gpx-converter package for Python was used for creating the maps. In total, 802 163 samples (at a sampling rate of 400 Hz), sorted by coordinates, were obtained, which is equal to approximately 33 minutes of car driving.

Graphs of acceleration versus time for three types of road surface are shown in Fig. 2. Graphs were built on 4500 values of the timestamp variable. Timestamp variable counts every 0.0025 second of the experiment, so it is slightly modified time scale. Sorting the data by the timestamp variable allows to arrange them in the correct order.

An analysis of the graphs in Fig. 2, *a* and *b* allows to conclude that, firstly, the nature of the dependences of accelerations on time clearly changes when the car moves on roads with different road surfaces and, secondly, these differences are visible even in a small section of the graph, that is, frames consisting of a small number of samples can be used, since in this work not an event, but a process is analyzed.

During the experiment, the speed of the car was not regulated. So, the data collection was representative of the real-world conditions when vehicle speed may vary on the same

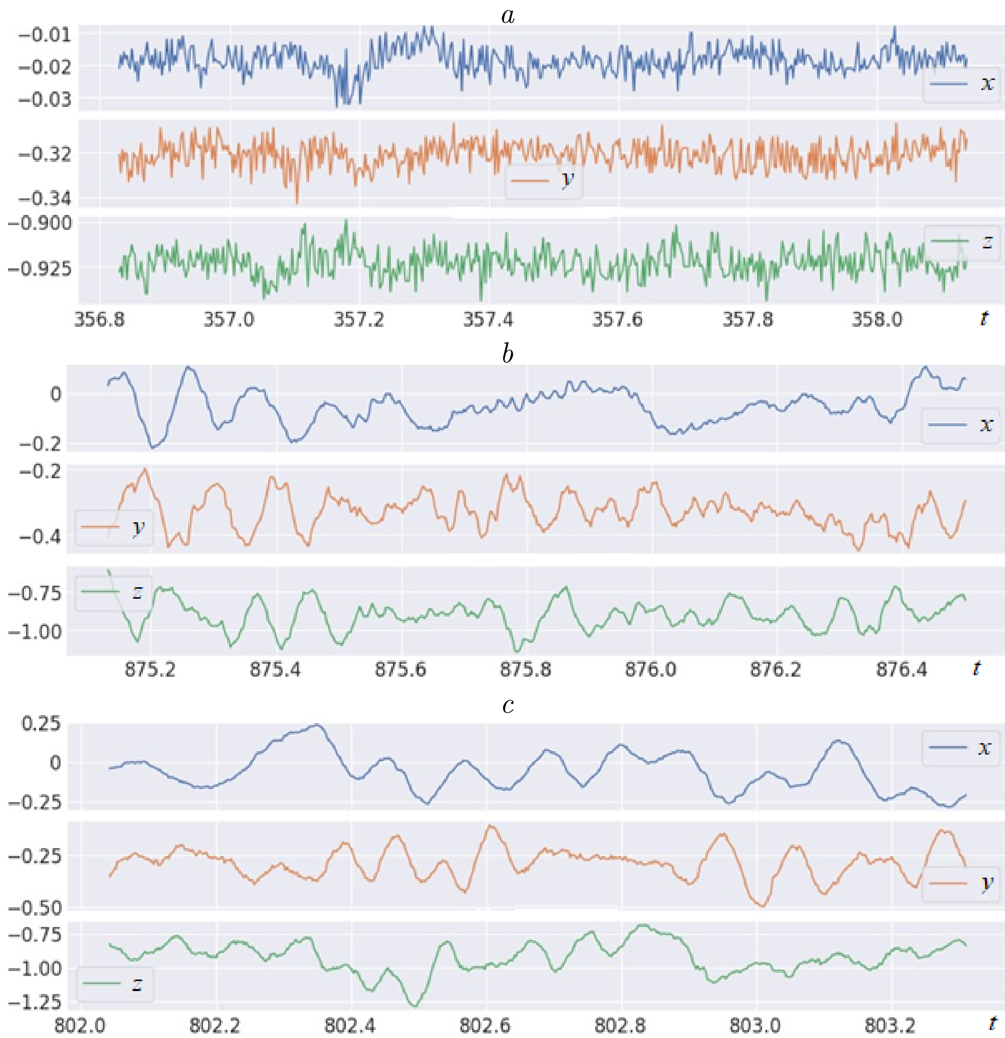

Fig. 2. Graphs of acceleration versus time for asphalt (a), gravel (b), and cobbled (c) roads

road segment. Frames were formed from 500 samples long, for a sampling rate of 400 Hz, which corresponds to 1.25 seconds of driving a car, with overlap (step 20). Thus, from a small dataset, it was possible to form 32 000 frames for training the neural network.

To implement the algorithm for identifying types of road surface, a network of long short-term memory was used. Architecture of the used single layer LSTM neural network is shown on Fig. 3.

The LSTM network is a network with feedback connections, it is well adapted to learning on the problems of classification, processing and forecasting of time series in cases where the samples that contain defining patterns are separated by ballast samples, and the ballast segment has indefinite duration and boundaries. To improve the performance of the model, a bidirectional LSTM network was used. Unlike a conventional LSTM network, a bidirectional LSTM network is trained on both forward and backward sequences of input data.

A single layer LSTM neural network containing 256 neurons was implemented using the Keras library. The model was trained on 32 062 frames for 20 epochs with the following parameters: batch size = 64, validation split = 0.005. Fig. 4, a shows the results of neural network training. The graph of the learning process presented in Fig. 4, b shows that the neural network has achieved good performance by the 20$^{\text{th}}$ training epoch.

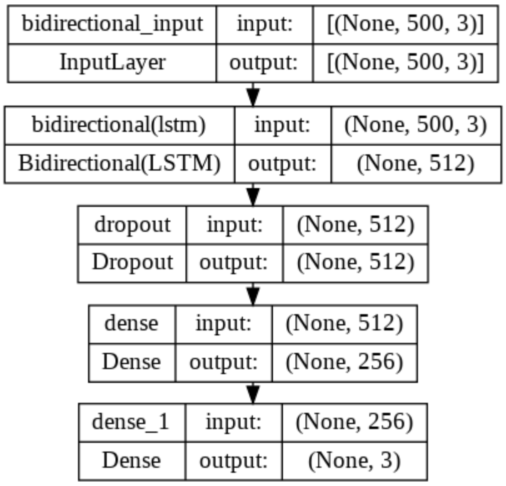

Fig. 3. Architecture of the used single layer LSTM neural network

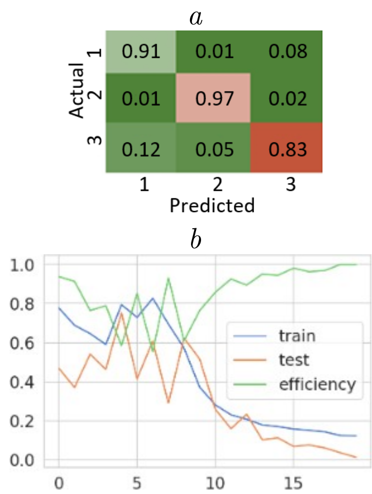

Fig. 4. Results of training a bidirectional single-layer LSTM neural network: *a* — error matrix, where the target variable corresponds to the type of road surface and takes three values: cobbled (1), gravel (2), and asphalt (3) roads; *b* — learning process graph

A single-layer LSTM neural network used to implement the task of determining the type of pavement has a number of significant advantages. The network learns quickly, achieving good performance with a sufficient sample and the trained model file size is a few megabytes.

Conclusion

The efficiency of identification of pavement types achieved in this work is 88.2 %. Analyzing the error matrix, it should be noted, that the largest number of errors occurs in sections marked as asphalt road sections, which the neural network erroneously identified as cobbled (519 error cases) or gravel (208 error cases) road sections. It can be seen that the errors are unevenly distributed. This view of the error matrix can be explained taking into account that in areas with asphalt pavement within the city there are inevitably bumps, including artificial ones, potholes, there was also a crossing over tram tracks on this route. In this work, a strategy was chosen to simulate the natural movement of a car within the city, so areas with ideal asphalt surface were not specially selected. Nevertheless, a fairly high accuracy of identification of road surface types has been achieved. In the course of further research, it is planned to use data from several passenger cars of different brands, since each vehicle has its unique response to the stimulus, created by driving on different types of road surface, and to expand the number of routes. It is also planned to compare the performance of identifying road surface types of convolutional networks trained on images obtained using a time series transformation gramian angular fields algorithm, the so-called GAF transformation, in which time series are converted from Cartesian to polar coordinates, and then are transformed into a GAF image [12], with the training results of a bidirectional single-layer LSTM neural network given in this paper.

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МАТЕМАТИЧЕСКОЕ МОДЕЛИРОВАНИЕ

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Применение нейросети для идентификации типа дорожного покрытия

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Аннотация

Цель. Решена задача определения типа дорожного покрытия (асфальтированная, гравийная дорога, мостовая) с использованием искусственного интеллекта.

Методы. Предложено использовать данные об ускорении по трем осям с инерциального измерительного модуля, помещенного в транспортное средство. Массив разделен на данные, полученные на трех разных типах дорожного покрытия путем фильтрации данных по географическим координатам. Всего при частоте дискретизации 400 Гц получено 802 163 отсортированных по координатам семпла, что равно примерно 33 минутам езды на автомобиле. Для реализации алгоритма идентификации типов дорожного покрытия использована сеть долгой краткосрочной памяти (англ. long short-term memory — LSTM) — разновидность архитектуры рекуррентных нейронных сетей. Однослойная LSTM-нейронная сеть, содержащая 256 нейронов, реализована с помощью библиотеки Keras.

Результаты. Эффективность идентификации типов дорожного покрытия, достигнутая в работе, равна 88.2 %. Проанализирована матрица ошибок. Большинство ошибок можно объяснить, принимая во внимание выбранную стратегию сбора данных: симуляция естественной езды на легковом автомобиле в черте города. Приведено краткое описание будущей работы по данной теме.

Ключевые слова: рекуррентные нейронные сети LSTM, инерциальный измерительный модуль, определение типа дорожного покрытия.

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