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# Automatic Evaluation of Pavement Thickness in GPR Data with Artificial Neural Networks

Y A Sukhobok<sup>1</sup>, L R Verkhovtsev<sup>1</sup>, Y V Ponomarchuk<sup>1</sup>

<sup>1</sup>Far Eastern State Transport University, Department of Computer Engineering and Computer Graphics, 47 Seryshev St., Khabarovsk, 680021, Russia

E-mail: yuri.sukhobok@gmail.com

**Abstract.** The ground penetrating radar (GPR) is one of the most frequently recommended non-destructive methods for the pavement thickness measurement. Due to the rapid growth of GPR data in the recent years, the development of automatic data processing techniques is required. In this paper we propose to use one type of artificial neural network, the multilayer perceptron (MLP), for automatic selection of the pavement boundaries. The experimental results indicate that machine learning techniques can be used for robust road structure evaluation.

## 1. Introduction

According to the Transport Strategy of the Russian Federation up to 2030 [1], it is necessary to develop and introduce innovative technologies in construction, reconstruction, and maintenance of the transport infrastructure, and to do research in order to increase the safety of the transport systems. Therefore, the task of organization of a pavement monitoring and implementation of new effective techniques for data analysis is of actual importance.

Pavement thickness has traditionally been determined by drilling and extracting cores, which is a considerably slow and expensive method that greatly damages the road structure. The use of non-destructive techniques (NDT) and near-surface remote sensing is required for road subsurface inspection, such as pavement thickness estimation, which is important for providing an accurate analysis in a relatively short time [2]. GPR is one of the most frequently recommended NDT methods for the pavement thickness measurements [3, 4]. This method is currently applied in many different areas such as geological studies, geotechnical engineering, civil engineering, archeology, mine detection, etc. [5, 6, 7]. It is rapid, cost-effective, and allows to be conducted without great impact on traffic [2, 4].

Due to the greater amount of highways, the GPR surveys require processing of the large volumes of the GPR data. In accordance with the standard [8], it is necessary to acquire at least two GPR profiles for each traffic lane. However, interpretation of the GPR data is usually manually performed that leads to significant reduction in processing speed, high level of subjectivity and dependence on the researcher's experience [2, 3]. Therefore, the GPR method requires the development of automatic data processing techniques, which would be applied to the road subsurface surveys.

The processing of the data of pavement layer thickness measurements is usually based on the semi-automatic horizon picking techniques with various selection criteria [2, 9]. Another approach relies on the different digital signal processing techniques. Some of them are based on the GPR traces spectral



analysis [10], the attribute or texture analysis [9, 11, 12], backscattered electromagnetic field analysis [13], kinematic and dynamic characteristics analysis [14].

In recent years, supervised machine learning and deep learning methods [15, 16] have been applied to the GPR data processing. For example, an application of convolutional neural networks is widely recommended [17, 18, 19]. Some papers [20, 21] describe the support vector machines (SVM) method for detection of the voids and cracks within the pavement. The authors of [22] describe the Viola-Jones learning algorithm for pattern recognition, which is applied in order to automatically localize reflection hyperbolas in GPR data. The paper [23] describes the usage of this method in combination with the artificial neural networks and support vector machines for the discrimination of layer boundaries between different rocks. Rodriguez [24] presented a prediction algorithm for features detection based on principal-component analysis and artificial neural networks. Szymchzyk [25] applied the Laplace transform artificial networks with the aim to classify some geological structures.

The use of the artificial neural networks in solution of the given problem appears to be more promising, than classic approaches. In this study, we aim to apply artificial neural networks to obtain an appropriate model for automatic selection of the interface boundaries in the GPR pavement inspection.

## 2. Materials and Methods

Fig. 1 shows the main procedure, which is followed in this study. We applied several types and architectures of neural networks (NNs), based on multilayer perceptron (MLP), 1D-convolution NN (CNN) and recurrent neural network with LSTM neurons [26]. These NNs were implemented using Keras (Tensorflow backend) with Intel® Core™ i7-4770K CPU, 32GB random access memory (RAM), and Nvidia GeForce GTX 1050Ti 4GB GPU.

### 2.1. Generating Datasets for the Artificial Neural Network

A high-quality GPR dataset was required to train the artificial neural network. The survey was conducted on the test site along the highway "Amur" (Chita – Khabarovsk). About 60 km of continuous GPR profiles of pavement layers were collected. The total volume of the source files was about 9 gigabytes.

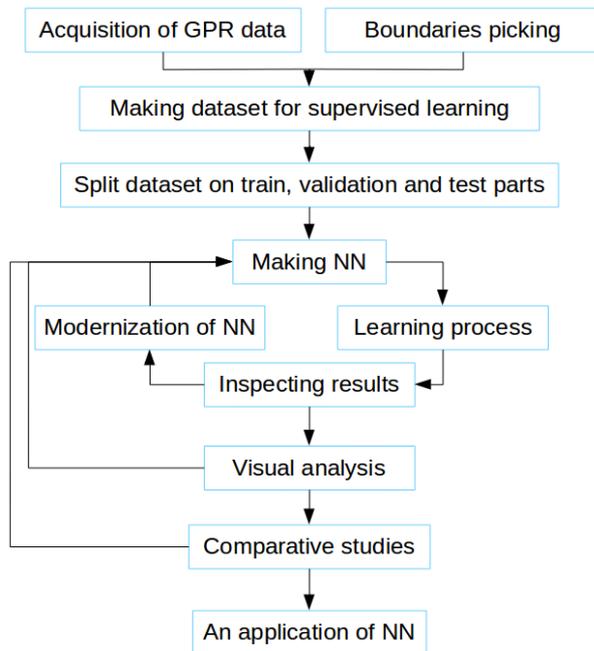
In order to collect the data the GPR system was used, which consisted of OKO-2 with 1 GHz air-coupled antenna from manufacturer Logis (Moscow, Russia). Data acquisition was carried out using the common-offset mode, and the parameters selected for acquisition were as follows: the total time window of 32 ns, 422 samples per trace, and 150 mm trace-intervals. The GPR data were acquired on an in-service road along the center line and along the road borders. The global navigation satellite system (GNSS) receivers were used to navigate the GPR system across the site. The pavement structure was composed of two layers of materials: asphalt concrete and crushed stone with the sand mixture. The example of the raw GPR trace is shown in Fig. 2, a.

We prepared three different GPR datasets that were obtained using normalization (Fig. 2, b), non-linear transformation to uniform distribution (Fig. 2, d) and non-linear transformation to normal distribution (Fig. 2, c), respectively. After that, the datasets were separated into the train and test datasets in the ratio of 80% and 20%, respectively. The size of the validation dataset was 20% from the train dataset. The trace samples count was limited with respect to the deepest point of asphalt concrete. The final size of the training dataset was about 875000 traces.

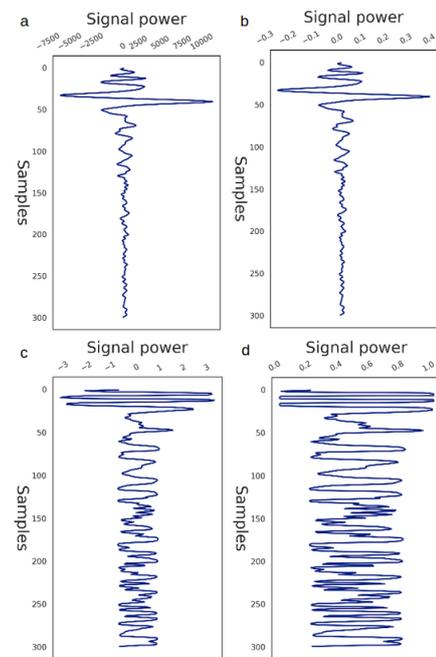
### 2.2. Artificial Neural Networks

In this section we present the analysis and selection of different architectures of a multilayer perceptron (MLP) for solution of the boundary detection task. This type of the NN was selected after theoretical study and practical implementation of 1D-convolution NN (1D-CNN) and recurrent NN (RNN) based on LSTM neurons. The filters of 1D-CNN go through the full vector of features where there could be more than one boundary, but there is only one marked layer in data. As for RNN, it did not process the data well because the data was interpreted using searching maximum/minimum phase

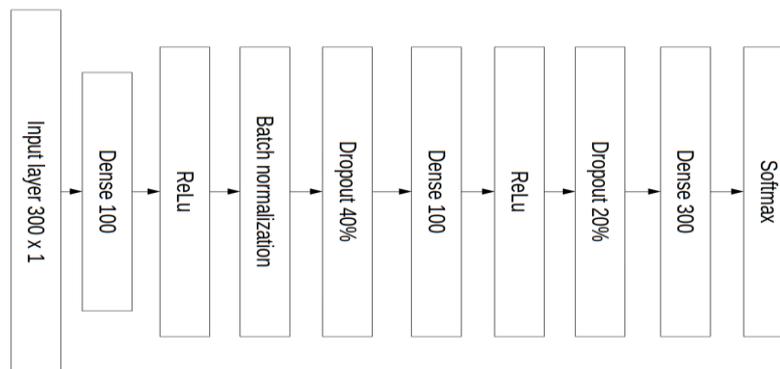
method, which partially destroys the correlation between the two adjacent traces. The results of the experimental evaluation of these NNs show that they are weaker in solving boundary auto-picking problem than MLP.



**Figure 1.** Flow chart of the NN development process.



**Figure 2.** Examples of the raw (a), normalized (b), non-linear transformed to normal distribution (c) and to uniform distribution (d) GPR traces.



**Figure 3.** The architecture of the suggested multilayer perceptron.

For training, the following hyperparameters were experimentally selected:

- batch size of 512 traces;
- batch normalization layer inside NN to increase the cumulative effect [28];
- Adam optimizer [29] with 0.01 learning rate and decreasing learning rate on a plateau by 10 times;
- number of epochs – 200;

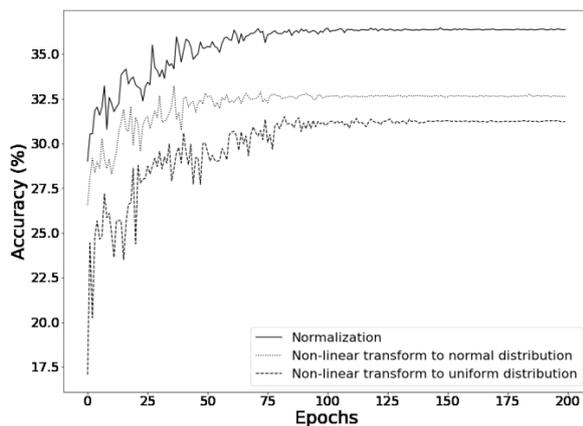
- 5 seconds average time for one epoch;
- 2 dropout layers with dropout rate 0.4 and 0.2 respectively [30];
- categorical cross entropy loss function.

The full architecture of the suggested NN is presented in Fig 3.

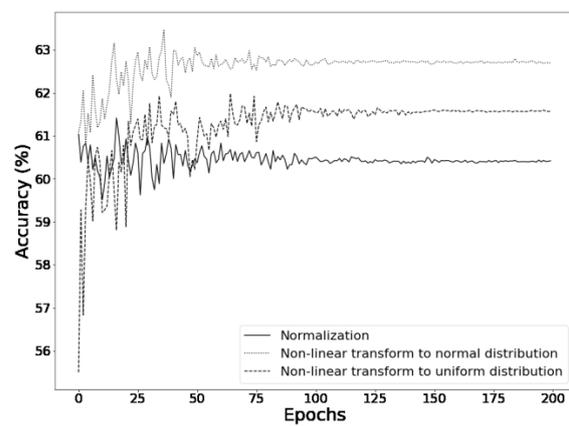
### 3. Results and Discussion

The results of the comparative analysis of the algorithms for raw signal preprocessing show that both linear and non-linear transformations are equally good. To evaluate the predictions of the neural nets we used absolute accuracy (standard metric), custom developed metric accuracy and visual analysis. The custom metric estimates the network prediction error; the accuracy values change linearly from 0, when the difference between boundaries positions is larger than 10, to 1, when boundaries are in the same position.

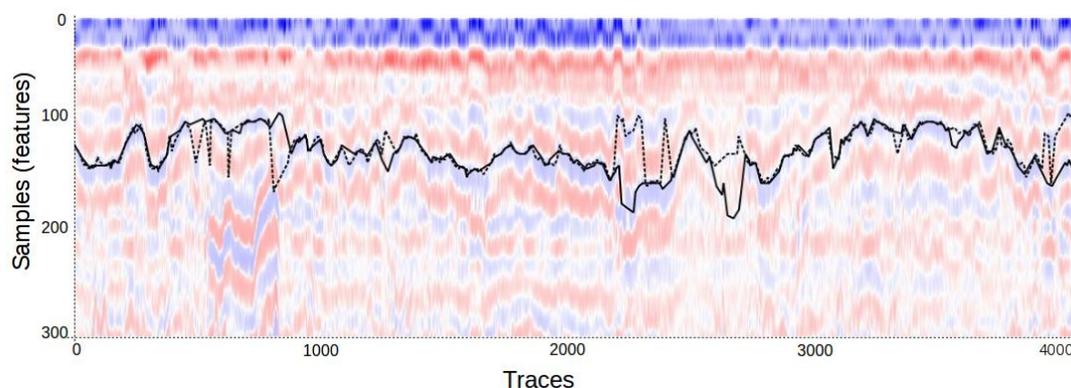
The Fig. 4 and Fig. 5 demonstrate the MLP architecture training process with different datasets. The analysis of these results shows that normalization is preferable when the standard accuracy metric was applied (35.5%). However, the nonlinear transformation to normal distribution produces the best results when the more adequate custom metric was used (63%). Theoretically, this means, that MLP, trained on the data with nonlinear transform, gives less prediction dispersion than MLP, trained on the normalized data. The visual analysis does not show any significant difference between the transformations.



**Figure 4.** Accuracy values in each iteration using standard metric.



**Figure 5.** Accuracy values in each iteration using custom developed metric.



**Figure 6.** Comparison of the neural network predictions (dotted line) and manual picking results (solid line).

Moreover, the speed of training and making prediction makes possible to use more complex architectures and ensembles of neural networks. For the present, MLP is able to make predictions for 9000 traces in 2-3 seconds. The lowest limit of prediction speed is about 10 predictions per second when real-time processing is required.

The results, which are shown in Fig. 6, allow to conclude that the NN is capable to make predictions which are very close to the human capabilities. Despite the high quality in boundary detection task with one boundary, MLP is very sensitive to displacement of patterns in the feature vector. Further, we are planning to use 1D-CNNs, that are invariant to the displacement of patterns, but this requires special data preprocessing.

#### 4. Conclusions

Currently, there is an obvious need in development of the methods for automatic detection of the interface boundaries in the GPR pavement inspections. We have developed and tested the MLP artificial neural network in order to solve this problem. The analysis of the experimental results shows the possibility of using the NNs for the GPR data processing. One of the main advantages of using machine learning to solve these types of problems is adaptability of these algorithms; that is, an increase of the number of manually processed data leads to the possibility of further training and gradual improvement of the results. Nevertheless, the MLP architecture places restrictions on the applicability. The perceptual field of this type of NN is very narrow. It means, that displacement of the boundary in the feature vector leads to a deterioration in the prediction result. So it is necessary to verify the suggested NN for some other GPR road inspection data.

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