PAPER • OPEN ACCESS

Practical aspects of using a neural network to solve inverse geophysical problems

To cite this article: A A Yakimenko et al 2018 J. Phys.: Conf. Ser. **1015** 032148

View the article online for updates and enhancements.

Related content

IOP ebooks™

Bringing you innovative digital publishing with leading voices to create your essential collection of books in STEM research.

Start exploring the collection - download the first chapter of every title for free.

Practical aspects of using a neural network to solve inverse geophysical problems

A A Yakimenko[1,2]**, A E Morozov**[1]**, D A Karavaev**[2]

[1] Novosibirsk State Technical University, 20, Karla Marksa St., Novosibirsk, 630073, Russia
[2] Institute of Computational Mathematics and Mathematical Geophysics SB RAS, Prospekt Akademika Lavrentieva 6, Novosibirsk, 630090, Russia

E-mail: yakimenko@corp.nstu.ru

Abstract. In this paper, an approach to solve an inverse problem of geophysics, such as determining the position of an object (cavity or cavern) and its geometrical parameters according to the propagation picture of a wave field, is proposed. At present there are no fast and accurate methods for determining such parameters. In this paper, a method based on neural networks (NNs) is proposed and a possible architecture of the NN is presented. The results of experiments on implementing and training the NN are also presented. The model obtained shows the presence of an "understanding" of the input data, demonstrating answers that are similar to the original data. In the NN answers, one can identify a relationship between the quality of the network response and the number of waves that have passed through the medium's object being investigated.

1. Introduction

Nowadays there are no instruments that allow fast and exact solving the inverse problem of geophysics. The inverse problem is understood as that of determining the structure and parameters of the medium under study from the available wave field propagation picture. One of the existing approaches to solving inverse problems is the iterative method: by gradually changing the parameters of a medium specified in a special program, the wave field propagation picture for the given medium is synthesized and compared with the available one. Then the parameters are changed towards the assumed optimum, that is, a set of parameters of the medium corresponding to the wave field picture that was taken. As a result of multiple repetition of this operation, one can reach the required parameter values. In this approach, much time for modeling and comparing wave field pictures is needed. The simulation time, depending on the accuracy and detailing of a model, can take up to several days even on powerful supercomputers.

To solve the problem of determining the locations and geometrical properties of objects, neural networks, which have turned out to be useful in various fields, from image recognition to time series processing, are proposed. It is assumed that the use of properly trained neural network structures will allow obtaining models that require less time for processing and determining the location and form of the desired inclusion, caverns (hereinafter referred to as cavernous media).

In this paper, it is proposed to use the NN for determining the structure of a geophysical model (GM) given in the form of a two-dimensional image. The image shows a homogeneous medium with a

cavity (cavern) whose center is located at an arbitrary point inside the medium. In this article, the cavity is understood as a round or oval-shaped one with arbitrary linear dimensions. For every GM, the forward geophysical problem of simulation of elastic wave propagation was solved previously. According to the results, it is proposed to reconstruct the geometry of the medium under investigation.

2. Architecture of the neural network

The wave field propagation picture in a medium in the form of a sequence of two-dimensional colored images as input data for the neural network is used (see Figure 1). Such images (snapshots) are taken at regular time intervals. The model is a 2D homogeneous medium with a cavity inclusion. The linear size of the model is 5 km along the Ox-axis (horizontal) and 1 km along the Oz-axis (vertical). The snapshots are presented for the vertical component of the wave field. The elastic medium and the inclusion have different values of the elastic parameters. Therefore, one can observe elastic waves reflected from the inclusion or formed after passing the cavity.

The output data for the network should be the proposed GM in the form of a two-dimensional colored image used to solve the forward geophysical problem.

It should be noted that in some situations waves reaching the cavern or reflected waves have small amplitudes. In this case, it is much more difficult for the NN to recognize the cavity in the input data (see Figure 1).
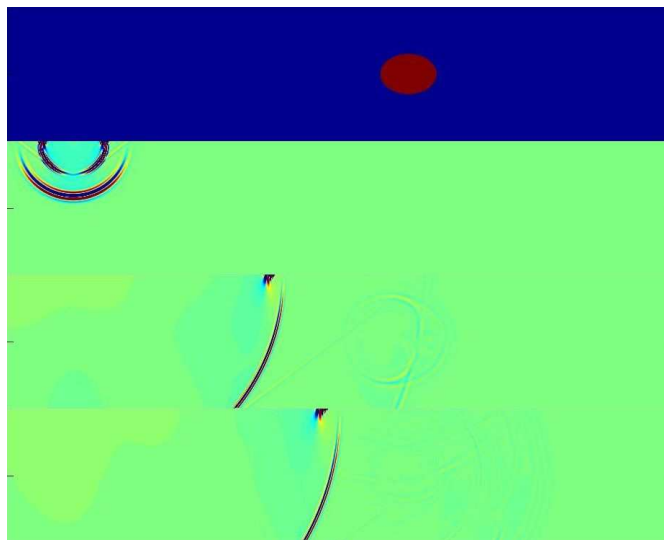
Figure 1. The structure of the GM with a cavity (the upper image) and wave field snapshots. Lower image depicts the last snapshot with waves of small amplitudes reflected from the cavity.

When designing the NN, network architectures that turned out to be useful in solving various problems were used. Since image processing was needed, it was decided to use a convolutional neural network (CNN) [1]. This type of network allows one to obtain high-precision models when solving problems of classification and detection of objects in the image. To demonstrate the efficiency of the CNN, one can consider the results of experiments on recognizing hand-written figures using, as an example, the Mixed National Institute of Standards and Technology (MNIST) database [2]. With its help, a recognition accuracy of up to 99.77% was achieved [3].

Since a sequence of images is used as input data, it was assumed that some dependencies characterizing the presence of a cavity can be used. In this case the Long Short-Term Memory (LSTM) network was used as a determinant of the presence of the dependencies [4]. This network has turned out to be useful in solving problems of processing of time series and images, analysis of the

sound, processing of the language, and many other problems associated with various kinds of sequences.

As a possible architecture, the CNN for converting input images into a numerical vector characterizing the input data is proposed. It is planned to use this part of the NN as a "feature extractor" uniquely characterizing every image with the help of a vector. Then the sequence of the resulting vectors must come to the LSTM layer so that the dependencies can be identified in them. After a response from the LSTM layer is obtained, it must be interpreted in an image of the medium similar to the original. For this it is proposed to use the NN with a sweep, an operation similar to convolution in the CNN; however, the input vector gradually unfolds into a color image of the specified medium.

To implement the "feature extractor", it is proposed to train a fully convolutional neural network so that it repeats its own input. This network will be a convolution from the size of the input image to the size of the required vector and the sweep from the shape of the vector to the size of the input image. It is assumed that the NN trained to reproduce its own input taking into account its architecture can describe the input image most accurately with a numerical vector at its center. In the future it is planned to use only the convolutional part of the trained "feature extractor" for converting input images into vectors of numbers.

The next part, which is a "sweep" of the neural network, is a composition of the LSTM layer, the fully connected layer, and the image generator. The sequence of vectors formed by the "feature extractor" with the help of several snapshots of the wave field is used as input data for the NN block. The images of the medium of interest are used as output data for training. To train both parts of the NN, it is planned to use the root-mean-square error as a loss metric.

3. Experimental technique and results

As an experiment, it is planned to train the obtained architecture and then test it on the available data. It is planned to implement the NN using the Python language and the Tensorflow library [5]. The OpenCV library [6] is used to work with images, and the Tensorboard tool - to draw the graphs of the loss functions.

As a result of the training, a "feature extractor" of a rather high accuracy has been developed. To convert images of wave propagation into a sequence of numerical vectors, the convolutional part of the trained "extractor" was used. After that, all images were transformed (Figure 2).
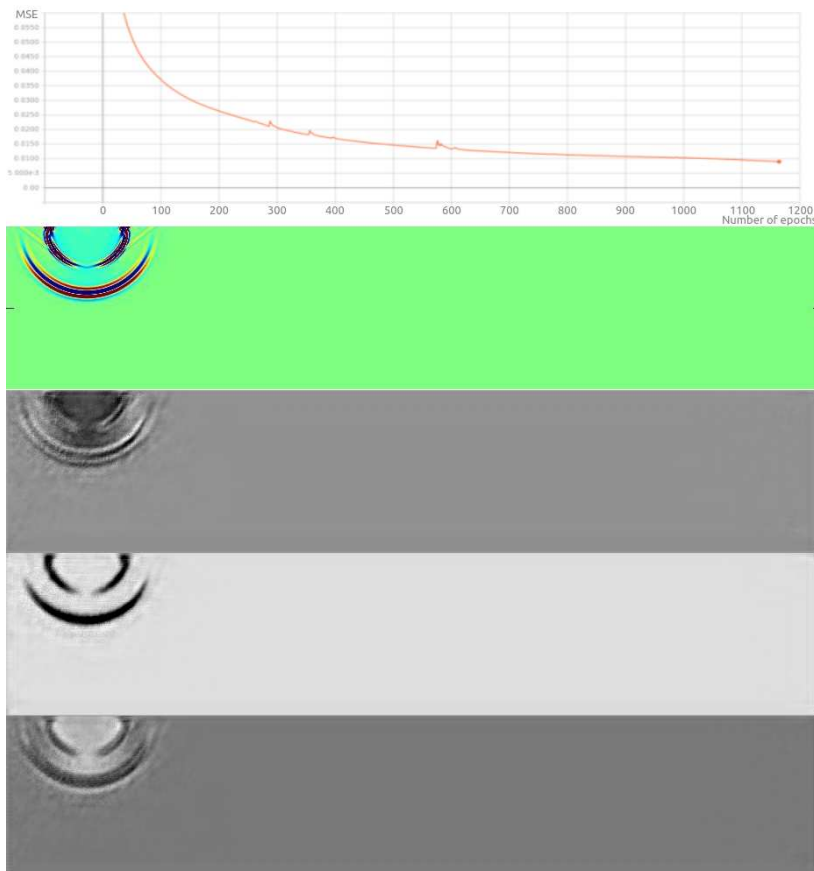
Figure 2. The loss function graph (upper image) obtained during the training of the "feature extractor" to reproduce its own input and an example of reproducing the input image for every color channel in RGB format.

After the transformation of images (Figure 3), the main part of the NN where sequences of vectors played the role of input data and the required models, the role of output data was trained. The trained model of the NN capable of reproducing the structure of the medium based on a set of numerical vectors corresponding to the sequence of images of wave field propagation was obtained.
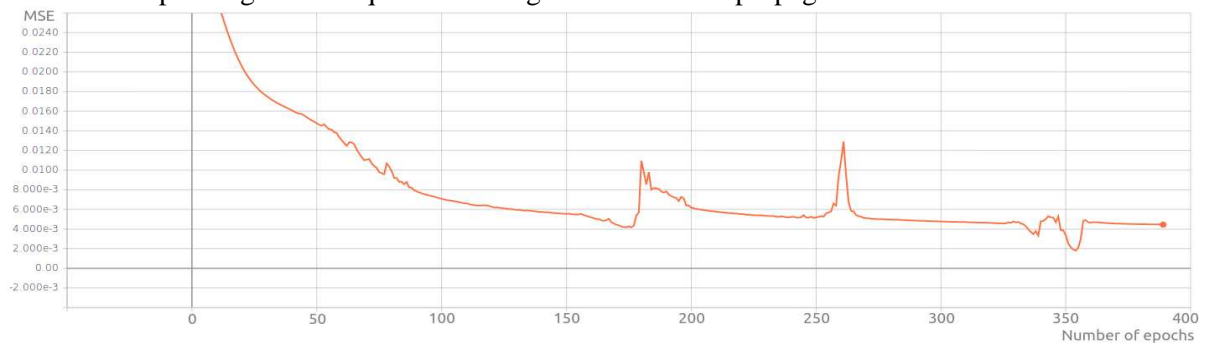
Figure 3. The loss function graph obtained during the training of the main part of the NN responsible for the cavity image reproduction.

On the basis of the results, it can be concluded that the implemented model determines the geometrical shape and the cavity location rather accurately. Comparable results, both for round and oval cavities of different sizes, were obtained.
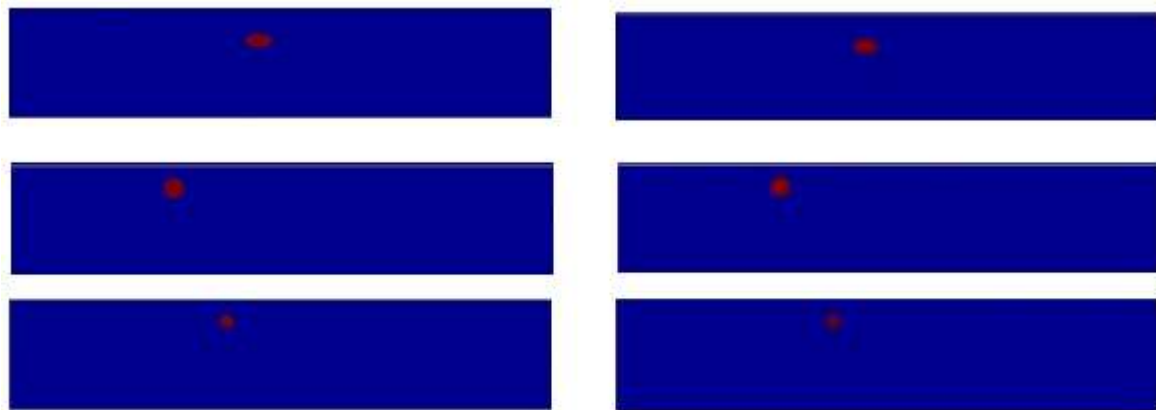
Figure 4. Examples of investigated models (left panel) of elastic media and responses obtained by the NN (right panel).

Figure 4 shows that the model has learned to recognize the parameters of the medium from the wave field images rather accurately.

It should be noted that for some media the NN could not accurately reconstruct the cavity (Figure 5). Analysis of the input data has shown that the cavity was quite far from the signal source and reflected waves of small amplitudes could be obtained.
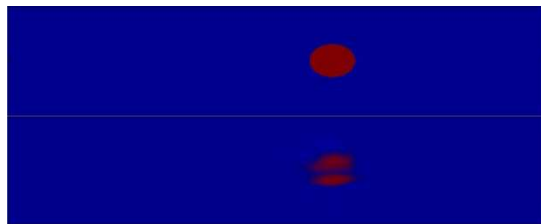
Figure 5. An example of medium structure reconstruction with a "phantom" object. Reconstruction was performed with the help of the NN determined by the input data with small amplitudes of reflected waves.

4. Conclusions

In this paper, the possibility of using the neural network tools for solving inverse geophysical problems to determine the positions and geometric shapes of objects using cavernous media as an example has been demonstrated. To obtain more accurate results, the neural network must be trained with a large number of input data (at least 100 different GMs and the corresponding solutions of the forward geophysical problem). In the future it is planned to train the NN to identify GMs with complex subsurface structures and develop an algorithm to eliminate "phantom" objects. A program to simulate elastic wave propagation in two-dimensional inhomogeneous elastic media was also developed. This program is based on a fourth- order finite-difference method with respect to space [7, 8]. The program has parallel implementation for calculations on high-performance computing systems constructed with GPUs. All calculations to solve the forward geophysical problem and obtain wave field snapshots for the NN training were made with the developed parallel algorithm and the program code for GPUs on the hybrid cluster NKS-30T of Siberian Supercomputer Center of the Siberian Branch of the Russian Academy of Sciences, http://www.sscc.icmmg.nsc.ru.

5. Acknowledgments

References

[1]   LeCun Y and Bengio Y 1995 Convolutional Networks for Images, Speech and Time-Series *The Handbook of Brain Theory and Neural Networks (MIT Press)*

[2]   Gavrilov A V and Maliavko A A 2017 Key-Threshold based spiking neural network *Proc. of the 2 Russian-Pacific conf. on computer technology and applications (Vladivostok)* (IEEE) pp 64-67

[3]   Cireşan D, Meier U and Schmidhuber J 2012 Multi-column Deep Neural Networks for Image Classification *Computer Vision and Pattern Recognition* pp 3642-3649

[4]   Hochreiter S and Schmidhuber J 1997 Long short-term memory *Journal Neural Computation* **9 (8)** 1735-1780

[5]   2018 An open-source machine learning framework for everyone. Retrived from: https://www.tensorflow.org/

[6]   2018 OpenCV. Retrived from: https://opencv.org/

[7]   Levander A 1988 Fourth-order finite difference P-SV seismograms *Geophysics* **53** 1425-1436

[8]   Moczo P, Robertsson J and Eisner L 2007 The finite-difference Time-Domain Method for Modeling of Seismic Wave propagation *Advances in Geophysics* **48** 106