Features of the Neural Network for Determining the Position and Geometric Characteristics of Cavernous Inclusions

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***Abstract* — This article describes the process of developing a neural network (NN) capable of restoring the structure of the geological and physical model of the medium (GPMM) based on a known picture of the propagation of a wave field. The architecture of the NN itself and its components are indicated, information on the process of its training is provided. Also, the time of operation of the NN on different devices and the results obtained are shown. The work was supported by the Novosibirsk State Technical University (Project C-19, 2018).**

***Index Terms* — Neural network, wave field, geophysics, cavern, inverse problem.**

I. Introduction

THE PROBLEM OF RECONSTRUCTING the GPMM structure from the wave-field propagation pattern can be considered as the task of analyzing the sequence of images. There are known NN architectures in which convolutional layers are used to transform an image into a number vector and recurrent layers to analyze the resulting sequence of vectors. [2, 3] As an example, we can cite the HC realized in [1]. In this case, each cell of the recurrent LSTM layer has a separate convolutional neural network. In this article, the network has shown good results in tasks of activity recognition, description of a single image and description of the video stream.

The architecture presented in [1] has a drawback: with the increase in the number of cells in the LSTM layer, the number of convolution models also increases, and therefore the total number of variable parameters of the NC increases, which leads to more occupied RAM. Also, when processing this model, time.

II. Problem Definition

According to the existing picture of the propagation of the wave field, to reconstruct the structure of the geological and physical model of the medium, over which the signal propagation took place. As input, there is a sequence of field propagation images. At the output, it is proposed to obtain an image of the desired medium.

III. Theory

A. Development of a Neural Network

When developing the NN for the solution of the problem, the model from [1] was used as the basis, however, many convolutional models at the input of the recurrent LSTM layer were replaced by one deep model, an image analyzer trained to represent all images of the wave field propagation in the form of a number vector equally well.

The sequence of numerical vectors obtained as a result of processing all the images of the wave field and representing the process of propagation of the wave field in the medium is fed to the input of the LSTM layer. It should be noted that this layer of the network is specially adapted to work with sequences in which there are some short-term or long-term dependencies [4].

The result obtained with the LSTM layer is transferred to the restorer, which interprets it in the image of the medium over which the signal passed.

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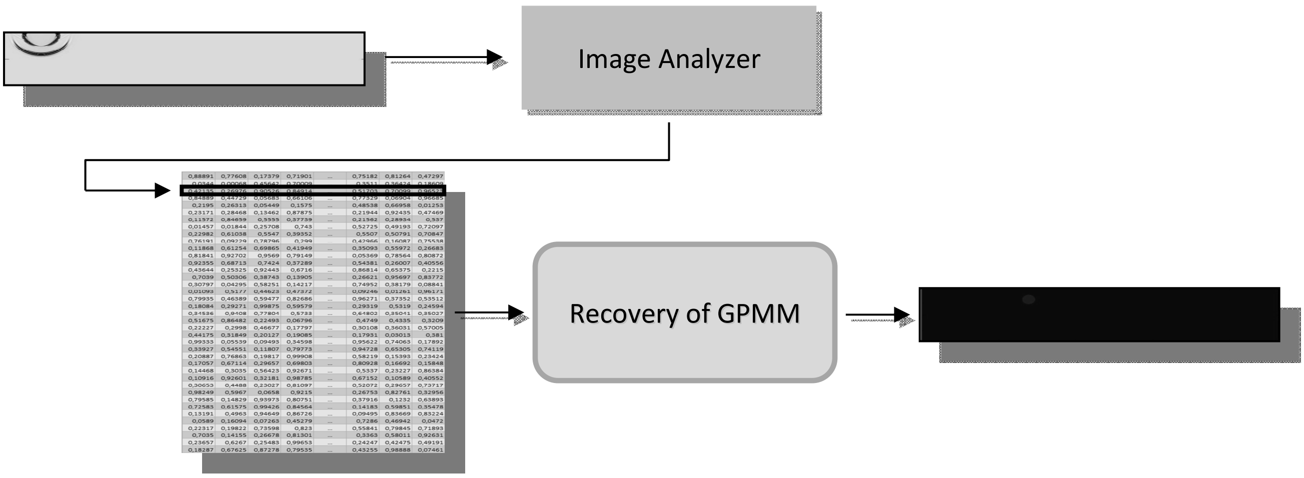

Fig. 1 General architecture of the NN. The images of the wave field are compressed by the analyzer into a numerical vector, after which the obtained sequence of vectors is transferred to the GPMM reducer, which gives out the assumed structure.

B. Neural Network Training

The learning process of the NN was carried out in three stages:

1) Image analyzer training
2) Formation of input data for the reductant using a trained image analyzer
3) Training of the reductant

The image analyzer was implemented using an autocoder - a neural network having a narrowing in its center, which is trained to reproduce its own input. The key point here is that at the end of the training, the network that best learned to reproduce its input can produce the most representative numeric vector in which the image is encoded at the narrowing point. At the end of the training, the network can encode the image into a form of numbers from which it can later easily recover it. A ready-made image analyzer is the first "encoding" part of the autocoder.

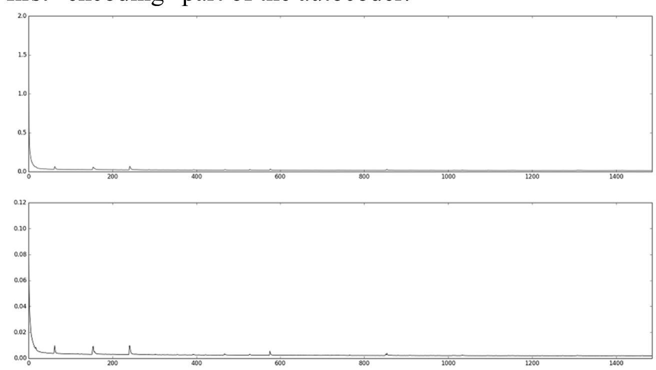

Fig. 2 Loss function graphs obtained during the training of the image analyzer at different epochs. The upper graph is the value of the loss function on the training sample. The bottom graph is for the test plot. As the loss function, the mean square error was used.

After training the analyzer, the wave-field propagation patterns for each GPMM were transformed into an ordered sequence of numerical vectors. Thus, the input data for the reducing agent were obtained. At the output, the reductant had to give out the image of the GPMM, which, according to the network, the signal propagation took place.

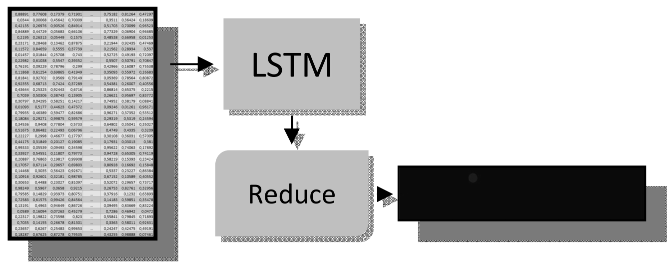

Fig. 3 Reductor architecture. The sequence of vectors is transmitted to a special recurrent layer of the neural network, after which the output from this layer is processed by the structure restoring part, consisting mainly of the scanning operation.

To train the models we used a personal computer with a graphics accelerator Nvidia GTX Titan with 12 GB of video memory and Pascal architecture. This accelerator was chosen because of the large amount of video memory, since stochastic gradient descent uses portions of input data of a certain size. The more data you can place on a video card, the more the right step will be made by the model in the direction of the global optimum in the space of its parameters.

A great deal of importance is also attached to the number of possible simultaneous threads, since this determines the learning time of a particular model. Due to the large number of learning parameters, the use of CPU and RAM for model training is impossible due to the small number of concurrent threads.

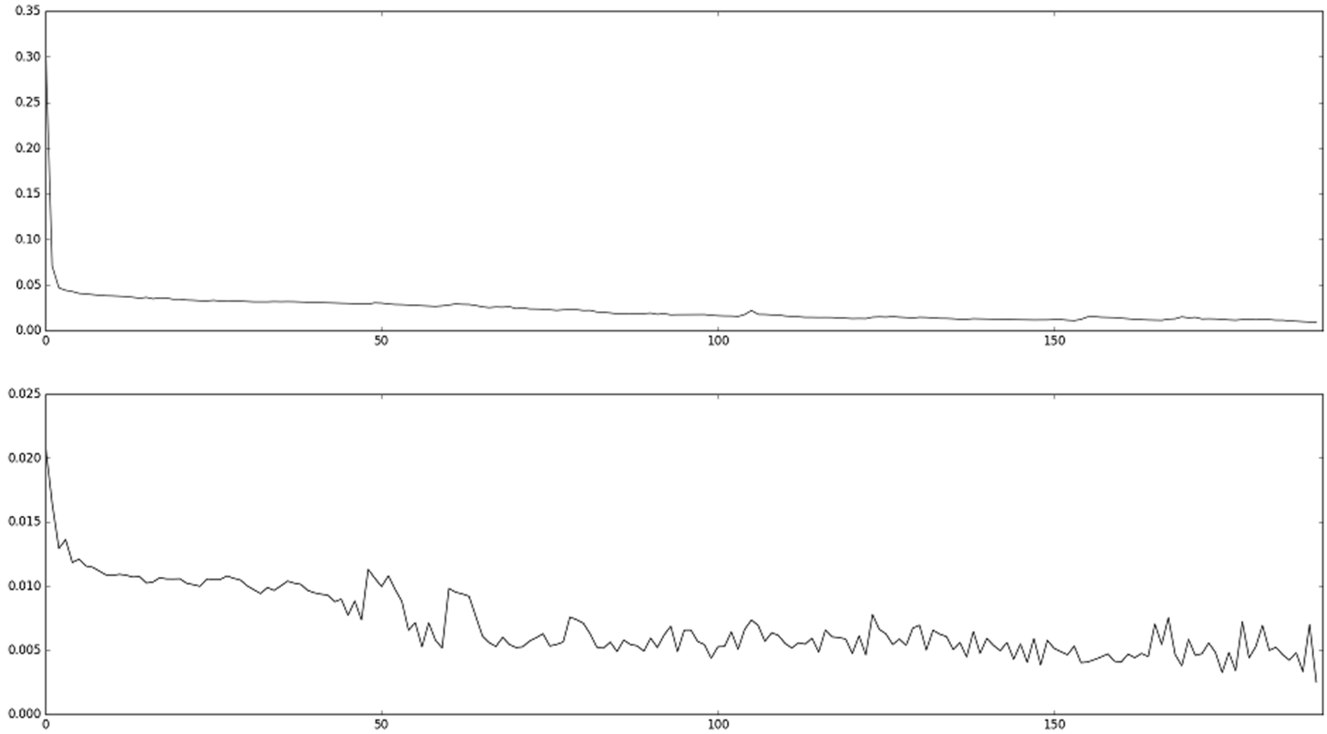

Fig. 4 Graphs of the loss function in the training of the reductant. The upper graph is the value of the loss function on the training sample. Lower - on the test. The function also used the mean square error between the images.

IV. Experimental Results

Results were not obtained from different models from the training and test sample. It can be seen that the implemented NN has learned quite well how to restore the GPMM.

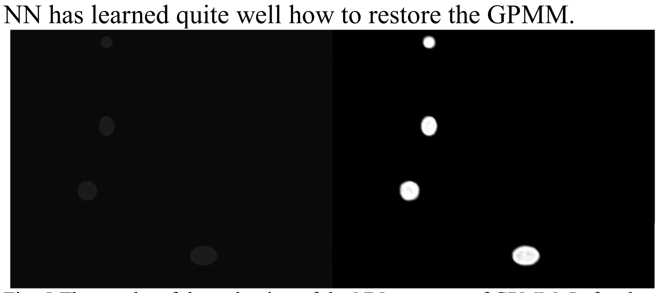

Fig. 5 The results of the reduction of the NN structure of GPMM. Left - the right answer. On the right is the result of the work of the NN.

It is also worth noting that when restoring some of the caverns of the network, it proved difficult to accurately determine their characteristics. Perhaps, a small number of pictures of the wave field at the time of the passage of the cavern itself or the analyzer's own error was transmitted to the restorer.

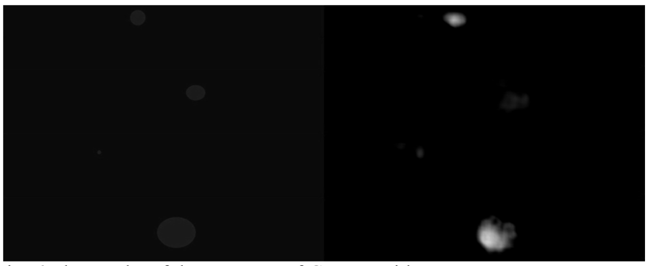

Fig. 6 The results of the recovery of GPMM with errors.

Below in Table I the time for network processing of several GPMM models on the CPU and on the GPU is given.

TABLE I

The Time Of The Neural Network Operation On The CPU And GPU

	CPU, ms	GPU, ms
Model 1	147	47
Model 2	149	50
Model 3	149	47
Model 4	145	48
Model 5	148	49
Average time	147.6	48.2

V. Features of the Platform

In order to obtain a more accurate NN model, it is planned to increase the number of convolution filters, both an image analyzer and a reducer, in the playback of GPMM. It is also planned to increase the number of bundles themselves, since a deeper model is capable of studying complex changes in the wave-field pattern.

VI. Conclusions

In each of the above HFMS models, the cavity was located at an arbitrary location and had an arbitrary shape and size, which shows that the processing time of the NS data does not depend on the geometric characteristics of the cavity.

The best architecture of the computer system for learning the model will be an architecture with as many GPUs as possible to increase the number of simultaneously processed streams and a large amount of video memory for a more accurate stochastic gradient descent of the model in the space of its parameters relative to the loss function.

It is recommended to teach a deep model on a large number of synthesized GPMM with a large number of images of the propagation of the wave field. Such an approach will make it possible to obtain an NN model more resistant to unexpected situations, which will accurately depict the required GPMM.

It is worth noting that the quality of recovery is highly dependent on the quality of the trained analyzer. In the implemented architecture, the error allowed by the analyzer is transmitted directly to the reworker and affects its operation. In the future, it is possible to change the architecture of the NN in favor of integrating the analyzer and the reductant into a single model, provided that the corresponding computing resources are available.

REFERENCES

[1] Jeff Donahue, Long-term Recurrent Convolutional Networks for Visual Recognition and Description 2016 Jeff Donahue, Lisa Anne Hendricks, Marcus Rohrbach, Subhashini Venugopalan, Sergio Guadarrama, Kate Saenko, Trevor Darrell

[2] Yann LeCun, Yoshua Bengio 1995 Convolutional Networks for Images, Speech and Time-Series

[3] Hochreiter, S., & Schmidhuber, J. 1995. Long short-term memory (Tech. Rep. No. FKI-207-95). Fakultät für Informatik, Technische Universität München.

[4] Gavrilov A. V. Key-Threshold based spiking neural network / A. V. Gavrilov, A. A. Maliavko, A. A. Yakimenko // Proceedings of the 2 Russian-Pacific conference on computer technology and applications, Vladivostok, 25–29 Sept. 2017. – IEEE, 2017. – P. 64-67. - DOI: 10.1109/RPC.2017.8168069.

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