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Application of neural networks in problems of determining geometrical properties of objects placed in geophysical elastic media

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Abstract. The use of a neural network approach is associated with high requirements for software implementation. The main criteria is a high degree of accuracy in the recovery of the desired geological-physical model of the environment (GPME) and processing speed. The paper presents a description of the developed neural network architecture for solving the inverse problem of geophysics for determining the geometric properties of GPME objects. The performance of a single neural network and an ensemble of neural networks (NN) has been evaluated. The results are presented comparing the operating time of the NN when restoring models on various computing devices: CPU and GPU. The results of experiments on the restoration of various GPME using the developed NN based on the LSTM layer and the U-Net architecture are presented. This work was supported by the RFBR grant No. 19-07-00170.

1. Introduction

The aim of the work is the development and study of a methodology that uses basically neural networks. This approach is used to solve the problem of reconstructing geological and physical models of media from wave field patterns [1]. To this end, we developed software for the implementation of the NN architecture and tested the developed neural networks. The results showed a good match with the original pictures of the models of GPME. Thus, the paper shows the high practical significance and applicability of the neural network approach to solving the inverse problem of geophysics. The solution of such a problem is connected with the restoration of 2D GPME and the determination of the geometric characteristics of the object in the form of a cavity located in the medium. Under the cavity should be understood as an oval region with non-zero values of elastic parameters. The elastic medium model is represented by a rectangular area in a 2D coordinate system. The case of an isotropic inhomogeneous medium described by three parameters is considered: two velocities of elastic waves and density. To train a neural network, it took the results of solving a direct geophysical problem of modeling the propagation of elastic waves in a 2D environment. As a result of a series of numerical experiments, a set of initial GPME models and a set of 2D field images were obtained. The presented calculation results are used as test data for testing the performance of the NN. 2D modeling of the propagation of elastic waves was performed using the computational resources of the Siberian Supercomputer Center of the Siberian Branch of the Russian Academy of Sciences: cluster НКС-30Т and НКС-1П.

Analysis of the wave field images showed that for high-quality NN work it is necessary to store information about the sign of the wave amplitude. The use of a three-channel image at the input of the NN leads to a significant increase in the amount of memory occupied by the model in the learning process. Therefore, when working with a neural network, it is necessary to convert a three-channel snapshot of the wave field into a single-channel one, while preserving the information about the wave amplitude.

It should be noted that the simulation results presented in the images are interrelated. The observed pattern of wave propagation of the current image depends on the picture in the previous image (iteration step in the calculation time). So The neural network must store certain information about previous images to form a qualitative opinion on the structure of the GPME.

It can be concluded that the target model of the neural network is faced with the task of analyzing the sequence of images for working with the wave field, as well as the task of segmentation to restore the position and size of the cavity.

2. Neural network development

2.1. Neural network training

To obtain a trained neural network model, it is necessary to solve the problem of optimizing the function defined by this model. First of all, it is necessary to determine the loss function, depending on the task set for the NN. The loss function is a function whose arguments are the correct answer to the input data set and the answer received by the neural network. When teaching NN its parameters tend to lead to such a form that the loss function takes the smallest value. In other words, when training a neural network, it is required to choose its weights so that the loss function takes the minimum value [2].

In order to apply gradient descent for training an NN, a backpropagation method was developed. It consists in propagating error signals from the network outputs to its inputs, in the opposite direction. This is achieved at the expense of the chain rule - the rule of differentiation of a complex function, which allows us to calculate the derivative of the composition of several functions on the basis of individual derivatives.

Using the method of back propagation of error, it becomes possible to study deep NN. Such NN have 2 or more layers in their structure. At the expense of the rule of the chain, the error during training extends from the output of the NN to its initial layers.

When teaching neural networks, stochastic gradient descent is widely used, since it offers an advantage in speed compared to standard gradient descent. When used, the value of the gradient is approximated by a gradient of the cost function calculated on one element of training [3, 4].

2.2. Data preparation

The size of the GPME and the obtained wave field images for teaching the NN was originally 929×186 pixels. It should be noted that the process of training the NN model to restore images of this size requires a large amount of computational resources — RAM and processor time. Therefore, to perform the work it was necessary to change the size of the input data in the form of images. First of all, the wave field and GPME were trimmed to sizes 736×184. It turned out that such a pruning did not spoil and did not remove the basic information, which reflects the presence of a cavity. Then the size of the images of wave field images and GPME was reduced to 256×64. This is for ease of operation and the need to use MaxPooling's operation. This operation is used to quickly increase the end-neurons of the field of perception. During this operation, the size of the incoming image is divided into two. Thus, the most advantageous dimensions of the sides of the input image for a model are multiples of 2. If one of the sides of the image is not such, at a certain stage of the model's direct passage, information about a row or column of pixels may be lost, since the division will be integer and the remainder of the division will be discarded.

For high-quality training of any neural network that works with images, first of all, the requirement is to have a large amount of training data. During the study, there was a problem with a small number of GPME for training. In total, there were 107 models, each of which had 14 snapshots of the wave field propagation.

To increase the amount of training data, noise from input images with normally distributed noise was used. For each GPME several copies were created, where the wave field patterns were noisy randomly. The mathematical expectation of the distribution of such noise was zero, and the dispersion was as small as possible and ranged from 10^{-8} to 5×10^{-8}. Using this augmentation method, the number of images in the training sample was increased from several dozen to 4–5 thousand. On such a number of images, the target model of the neural network could already be trained and highlight any patterns in the data to solve the problem.

2.3. LSTM-based architecture

To implement the model based on the LSTM layer, it was first necessary to create a neural network unit. Such a block is necessary to encode information from each snapshot of the wave field into a numerical vector. Then the vector can be transferred to the input of the recurrent layer. Simultaneous learning of such a model takes too much memory. The computing devices available for the job do not have the necessary resources. Therefore, the learning process of such a model consists of two stages. The first is the training of a wave field image encoder. The second is the training of the GPME restorer from a sequence of numerical vectors obtained using an encoder.

In order to get a quality encoder, he was trained on the principle of auto-encoder. The autocoder is a neural network that has a narrowing in its architecture and is trained to play its own input. Autocoders are widely used in solving various problems. In particular, when solving the problem of generating semantic numerical vectors for words (word2vec).

Figure 1 shows the structure of the simplest auto-encoder. In the place of narrowing of such an autocoder during training, such a numerical vector is formed, from which the model can then easily restore the original data. In this case, the appearance of the most representative numerical vector for the input data is said. After learning such an autocoder, its first part, before narrowing, can be used to encode the input data into a vector of smaller dimension. The first part of the autocoder is called the encoder.

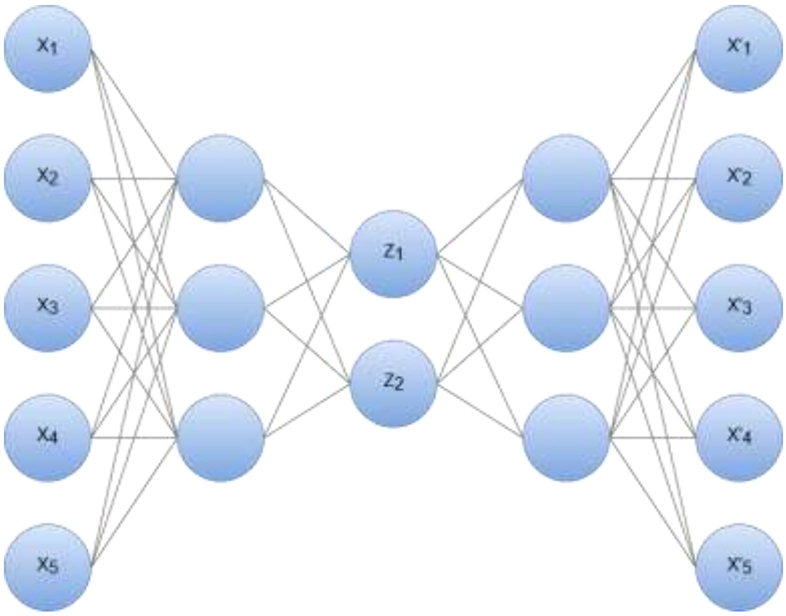

Figure 1. The simplest auto-encoder with a narrowing in the center on the example of NN from fully connected layers.

In the context of this task, the auto-encoder was assembled from convolution and pulling operations (encoder, first part) and sweep and anpuling (decoder, second part). The architecture of the auto-encoder was almost completely analogous to the architecture of the segmentation model of the neural network from [5], however, this technology was not applicable in this task due to the lack of data transmission over time within the model itself.

2.4. Reducer Architecture
The reducer of the GPME should have taken as input a sequence of numerical vectors created by the encoder and synthesize the GPME in which, according to his assumption, this is precisely the propagation of the wave field. Obvious was the need to use the operations of unpilling and scanning to realize the possibility of generating images based on numerical data coming from the LSTM layer [5]. During the direct passage of the model. Figure 2 shows the final architecture developed by the NN.

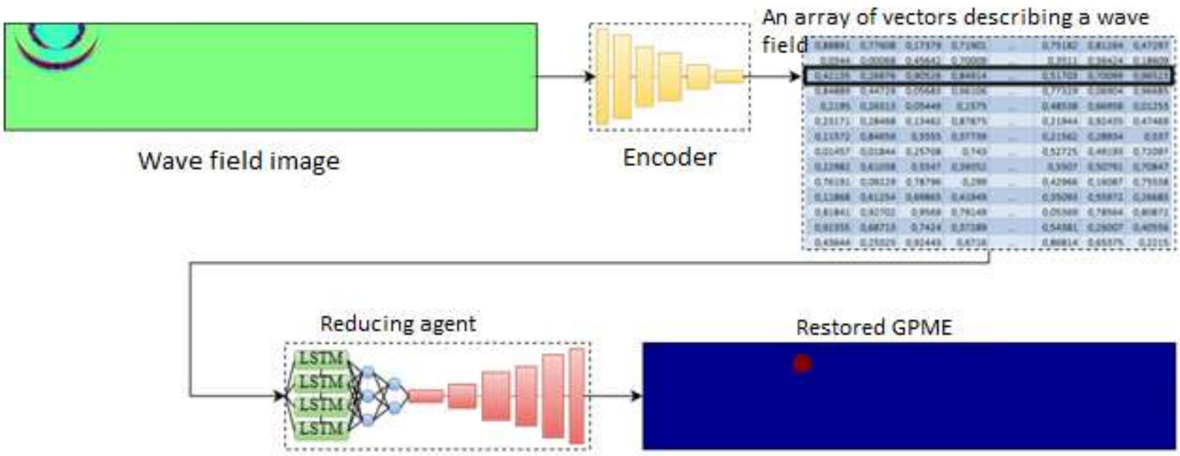

Figure 2. Developed NN architecture based on LSTM layer.

2.5. Restored GPME Architecture based on U-Net model
To build a neural network model based on the U-Net architecture [6], it was necessary to solve the problem of storing information in time from all incoming wave field images. To solve this problem, it was decided to add the output information from each level of the model after running each snapshot of the wave field. Each shot at the same time passed through the same weight. In other words, one encoder was used for all wavefield images, instead of separate encoders for each image. Subsequently, the sum of the encoded properties from each level was processed by subsequent layers of the model at the same level. Thus, from each snapshot that came to the input of the model, features of different levels were extracted, which were then used by the decoding part. Figure 3 shows the architecture of such a model.

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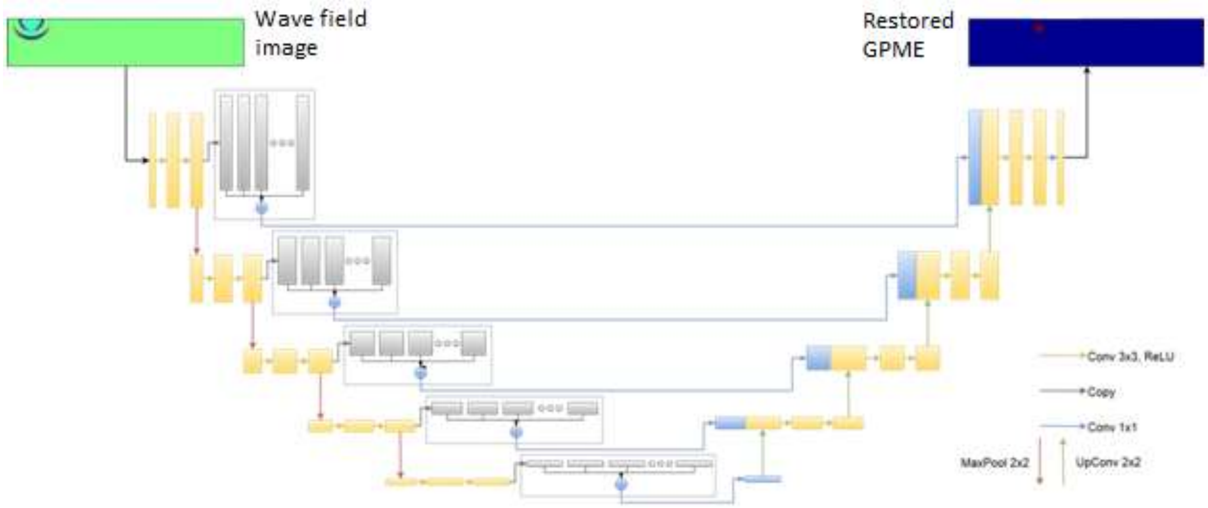

Figure 3. Designed by NS based on U-Net architecture.

3. Experimental results

3.1. Recovery examples

To confirm the quality of the recovery of the GPME with the developed models, experiments were carried out on the direct processing of wave field images developed by the NN, followed by visualization of the results.

The results of the restoration of the GPME on one wavefield pattern based on the LSTM layer (Figure 4) and the U-Net architecture (Figure 5) are presented. GPME models with different sizes and position of a cavity in an isotropic medium were considered.

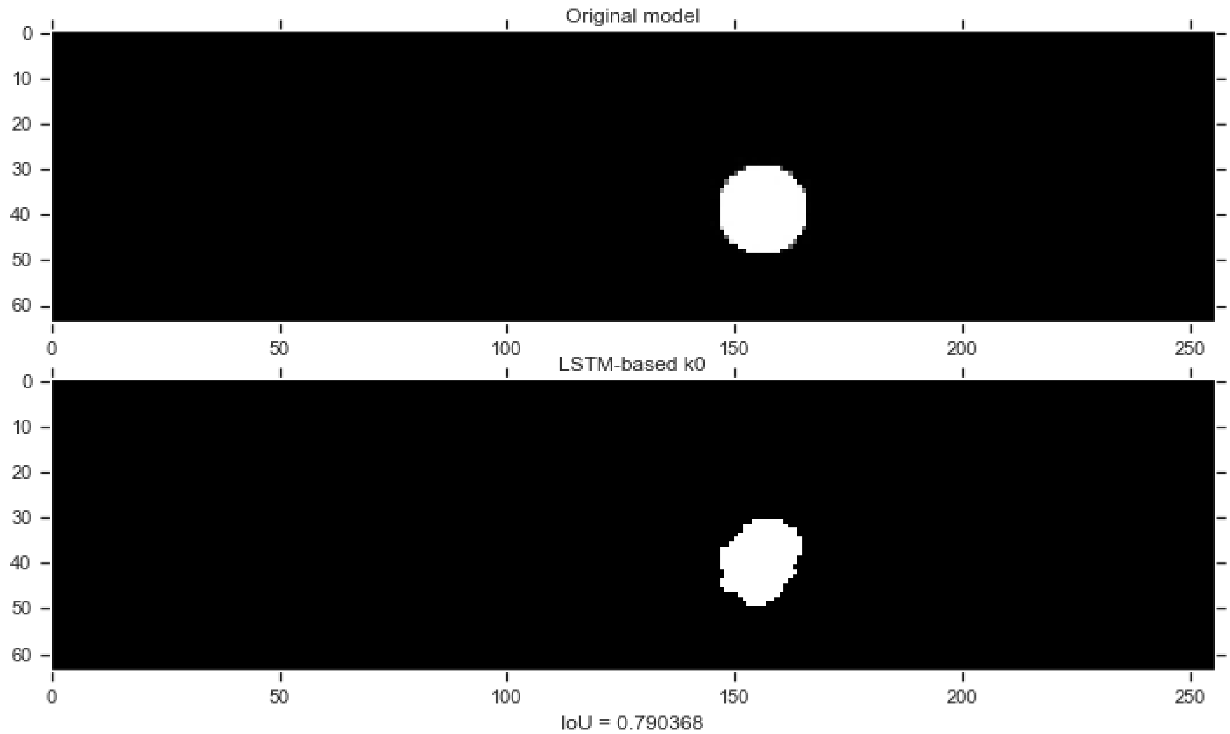

Figure 4. Result of restoration of the GPME based on the LSTM layer.

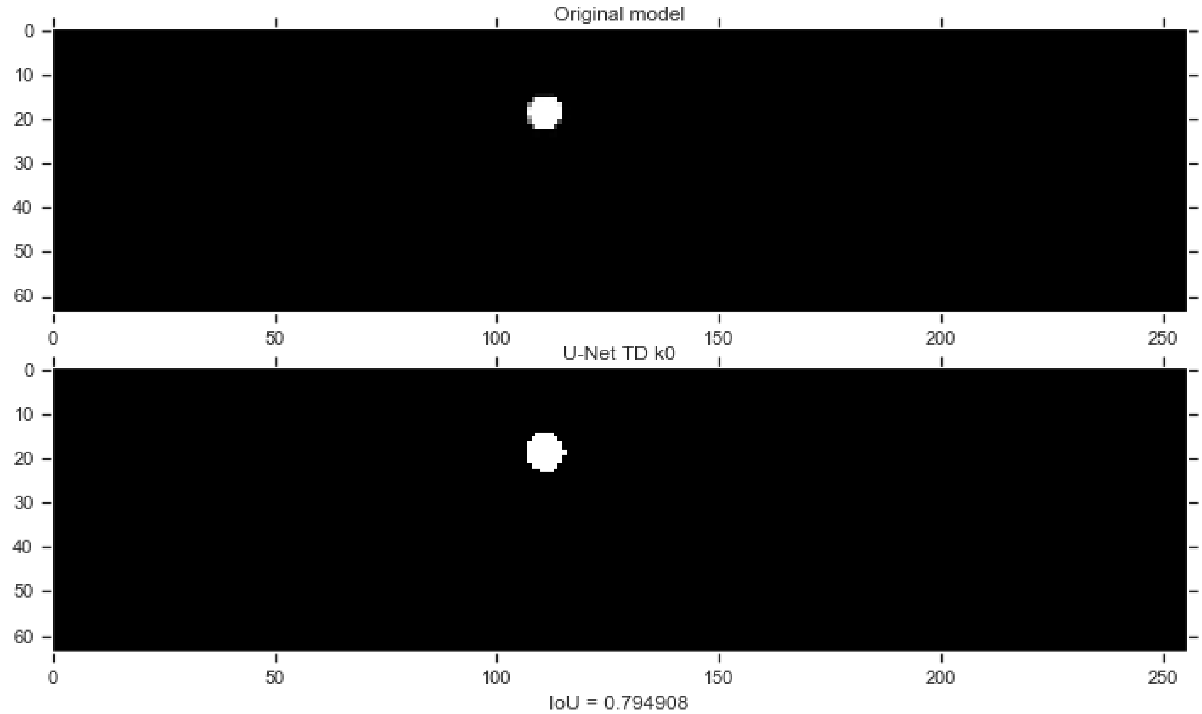

Figure 5. Result of restoration of the GPME based on the U-Net architecture.

Thus, when comparing the results presented in Figures 4 and 5, it can be seen that the model based on the U-Net architecture did much better than the model based on the LSTM layer. You can evaluate the quality of the restored model compared to the original. When using the U-Net, the oval area of the cavity is more fully restored.

3.2. Comparison of the working hours of the NN

The process of developing an NN is associated both with the quality of the results obtained and with speed. To compare the work of the presented NN architectures, experiments were carried out to restore models on different computing devices: a CPU and two GPUs. The main difference used by the GPU in the type and size of memory. The Nvidia GTX 850M is equipped with 4 GB DDR3 memory. Nvidia Titan X is equipped with 12 GB GDDR5 memory. The core frequency is also different. While the GTX 850M has a core frequency of 876 – 936 MHz, the Titan X has a core frequency of 1000 – 1089 MHz. All this gives Titan X an advantage in the processing speed of the NN model.

Evaluation of the execution time is carried out for single models and for their ensemble. An ensemble should be understood as a set of models that process the same data, whose readings are then averaged to improve the quality of their work.

In Figures 6, 7 shows the results of measuring the processing time of models based on the LSTM layer and the U-Net architecture on various devices.

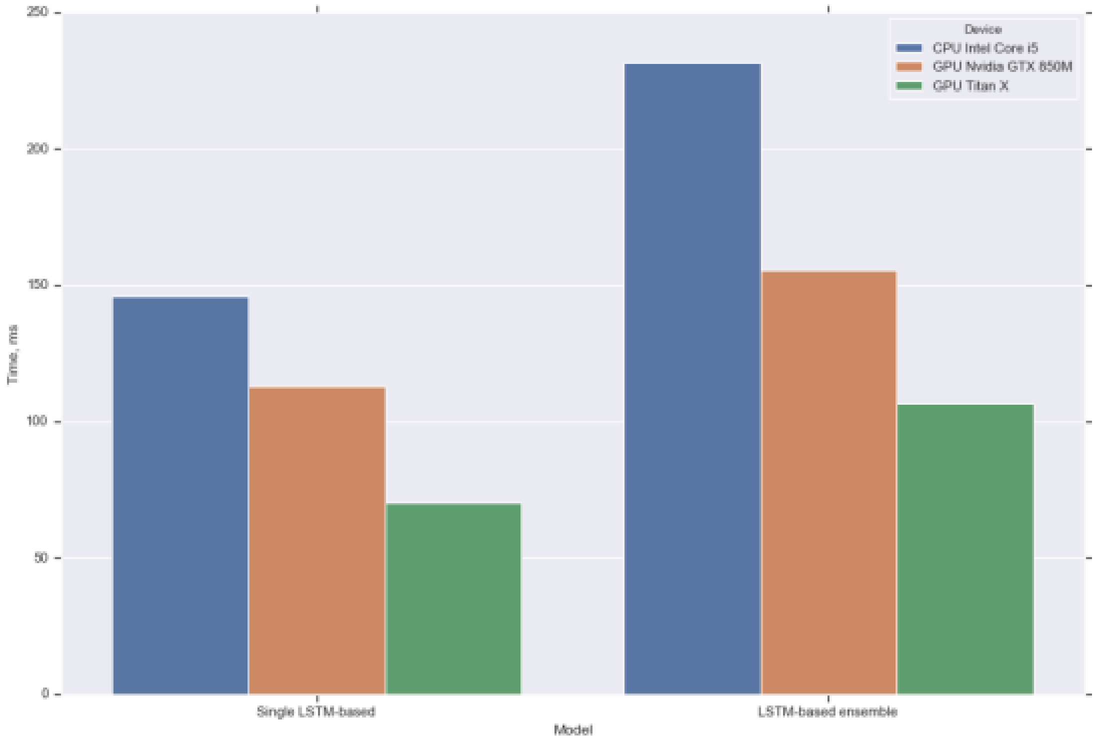

Figure 6. Measurement times for processing models based on the LSTM layer on various devices.

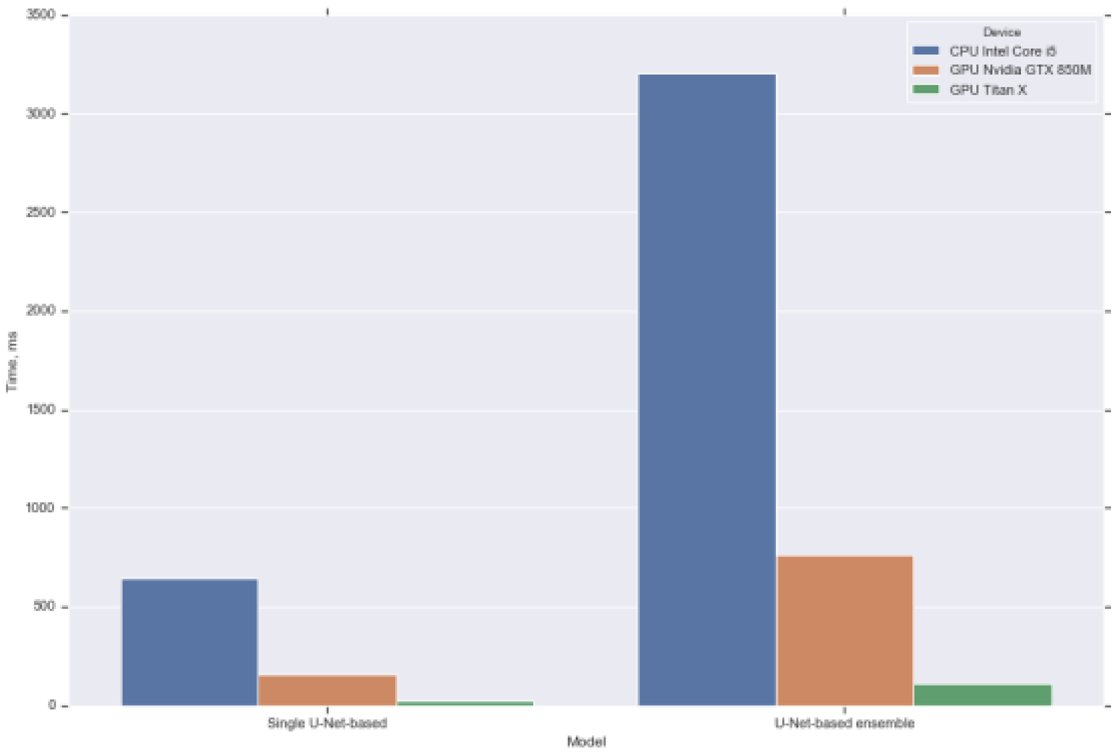

Figure 7. Measurement times for processing models based on the U-Net architecture on various. Devices.

Processing a single model based on the LSTM layer runs about twice as fast on the Titan X as on the Intel Core i5 CPU and about one and a half times faster than the GTX 850M GPU. When processing the ensemble, Titan X also wins. The processing time of the ensemble of models based on the LSTM layer on it is about 2 times less than on the CPU Intel Core i5 and one and a half times less than on the GTX 850M.

Processing a single model based on the U-Net architecture takes about 15 times longer on an Intel Core i5 CPU and 6 times longer on a GTX 850M than on a Titan X. Processing an ensemble of such models takes about 22 times more time on an Intel CPU Core i5 and 5 times more time on the GTX 850M than on the Titan X.

When comparing the results obtained between the two models, it was concluded that, on average, models based on U-Net architectures are processed longer than models based on the LSTM layer. However, the time difference is compensated by the demonstrated quality of the work of models based on the U-Net architecture.

4. Conclusion

The paper presents the architecture of the developed NN. The results of practical application of the developed NN architectures based on the LSTM layer and U-Net are shown. The features of the construction of such NN are described. The results of practical application of the developed software for the implementation of NN on test examples are presented. According to the obtained results, we can conclude that models based on the LSTM layer are processed faster than models based on the U-Net architecture. Also the ensemble of these models is processed much faster. This is achieved due to the fact that the coding part of this architecture only needs to process the wave field images that came to the model input once. After that, you can analyze the resulting sequence of vectors with different models of reducing agent to get the result of the ensemble. Models based on the U-Net architecture have no divisions with common parts, therefore, to analyze the wavefield pattern, complete processing is required for each U-Net-based model.

Despite the serious superiority of LSTM-based models in terms of processing time, both types of models are applicable to the on-site inspection task, since the processing time of a single model does not exceed 800 milliseconds, and the processing time of an ensemble of 5 models does not exceed 3300 milliseconds on a conventional dual-core CPU.

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