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Neural network recovery of missing data of one geophysical method from known data of another one in solving inverse problems of exploration geophysics

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This study is devoted to the inverse problems of exploration geophysics, which consist in reconstructing the spatial distribution of the properties of the medium in the Earth's thickness from the geophysical fields measured on its surface. We consider the methods of gravimetry, magnetometry, and magnetotelluric sounding, as well as their integration, i.e. simultaneous use of data from several geophysical methods to solve the inverse problem. In their previous studies, the authors have shown that the integration of geophysical methods allows improving the quality of the solution of the inverse problem in comparison with the individual use of each of them. One of the obstacles to using the integration of geophysical methods can be the situation when for some measurement points there is no data from one of the geophysical methods used. At the same time, the data spaces of different integrated geophysical methods are interconnected, and the values of the observed quantities (fields) for one of the methods can be possibly recovered from the known values of the observed quantities of another geophysical method by constructing a preliminary adaptive mapping of one of the spaces to another. In this study, we investigate the neural network recovery of missing data of one geophysical method from the known data of another one and compare the quality of the solution of the inverse problem on full and on recovered data.

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1. Introduction

The general statement of the inverse problems (IP) of exploration geophysics (EG) consists in constructing the distribution of the physical parameters of the medium in the thickness of the earth's crust from the physical fields measured on the earth's surface in order to study the structure of the near-surface layer of the earth and searching for useful fossils. In particular, in this study we consider the IP of gravimetry (G), magnetometry (M) and magnetotelluric sounding (MT), which consist in restoring the spatial distribution of density, magnetization, and electrical resistance of the medium in the Earth's crust by the values of gravitational, magnetic and magnetotelluric fields, respectively. These IPs are ill-posed, which generally leads to a low quality of the solution and high sensitivity to noise in the input data.

A general approach to reducing the ill-posedness of IPs is to change its statement. In the case of using machine learning methods, a change in the statement can be achieved by introducing some additional information. In this case, additional information can either fed to the input of the algorithm directly, or be used indirectly, by taking it into account when forming the training sample. An example of an approach associated with the indirect use of additional information can be the use of parameterization schemes with a rigidly defined spatial structure (the so-called "class-generating models" [1–4]), which is built on the basis of alternative measurement methods or on assumptions about the structure of the specific area. The disadvantage of this approach is the need to develop its own individual solution for each problem, as well as the need to have a priori information about the spatial structure of the defined parameterization. The method of direct introduction of additional information considered in this paper consists in setting the problem of integrating geophysical methods, i.e. simultaneous use of data from several geophysical methods to solve the IP EG [5–8]. However, in practice, it is possible that for some measurement points there is no data from one of the geophysical methods used. At the same time, the field data spaces of different integrated geophysical methods are usually to some extent interconnected, so the missing data of one geophysical method can be possibly recovered from the known data of another by constructing a preliminary adaptive mapping of one of the spaces to another.

The purpose of this work is to test the applicability of the approach associated with neural network recovery of the missing data of one geophysical method from the known data of another and their further joint application to solve inverse problem.

2. Physical statement of the problem

2.1 Parameterization scheme

In order to implement the integration of various geophysical methods, it is necessary that the determined parameters of each of the methods are the same. This approach corresponds to the geometric formulation of the problem, which consists in determination of the boundaries of geophysical objects. In particular, in this study we considered the parameterization scheme, which consists in determining the boundaries of geological layers of a layered medium.

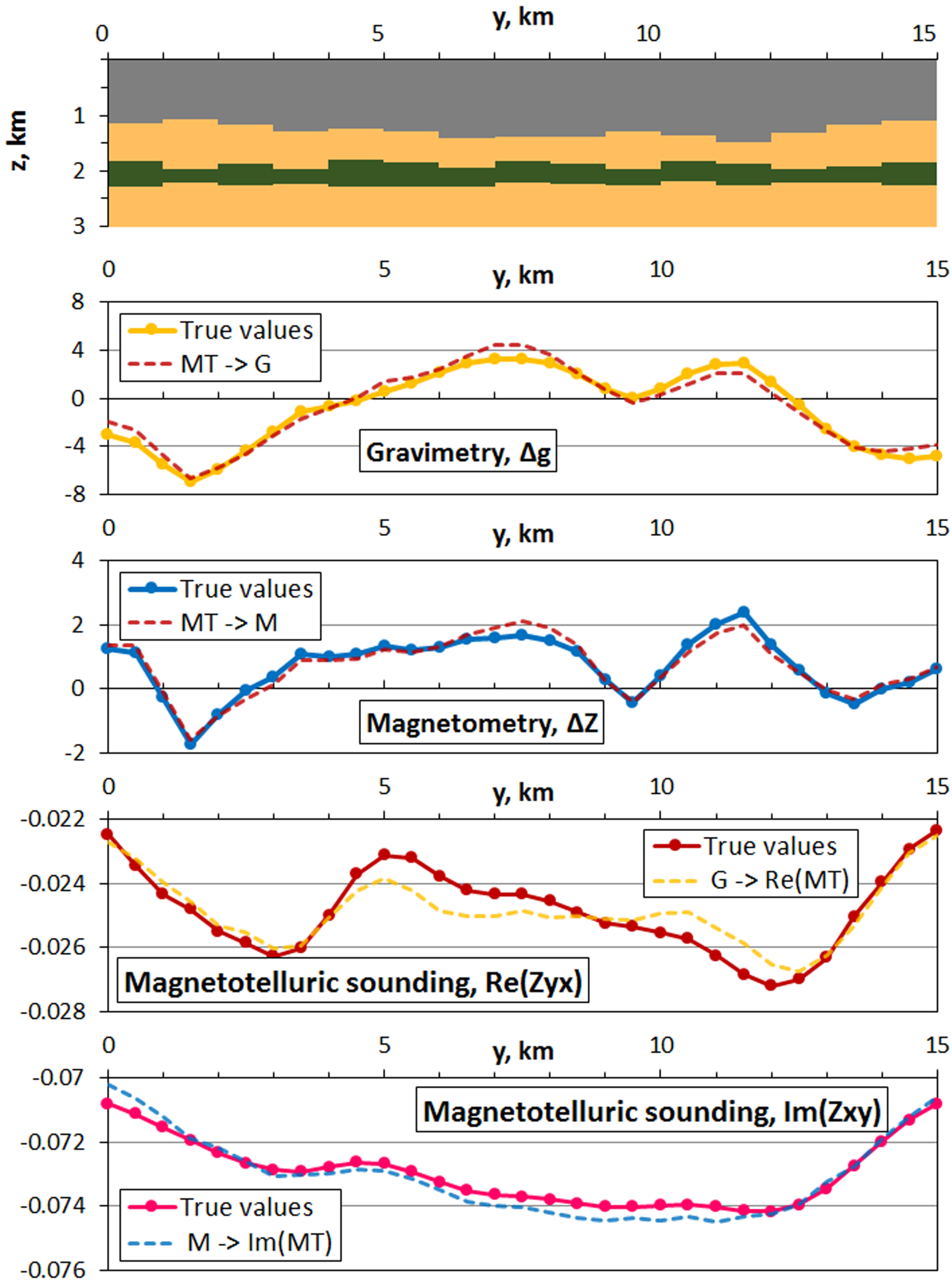

Figure 1: An example of the geological section within the considered parameterization scheme (top), and the corresponding components of the fields used in this study (bottom). Solid lines – true values of the field's components, dashed lines – recovered values.

The parameterization scheme was a four-layer two-dimensional model (Fig. 1) [8] – corresponding to a section of the Norilsk region. The first layer modeled the basalt layer, the second and fourth ones – terrigenous carbonate deposits of the Tunguska series, the third one – the gabbro-dolerites massive copper-nickel-platinum ores.

The dimension of the section was 15 km wide and 3 km deep. The physical field measurement step was 0.5 km – a total of 31 measurement points along the profile. The discreteness of changing the boundaries of geological layers was 1 km – a total of 15 depth values for each layer. In this problem, the values of the depths of the lower boundaries of the three upper layers were determined. Each layer was characterized by fixed values of density, magnetization, and resistivity, which did not change within the layer, and which were the same across the entire data set. The physical characteristics of the second and the fourth layers were the same. The discreteness of changing the values of depth was 0.02 km.

2.2 Data

For each pattern of the original data set, the layer depth values were set randomly in the given ranges. Further, the direct problem was solved by finite-difference methods for each of the selected geophysical methods.

The input dimension of the problem was:

- Gravimetry: 1 field component * 31 measurement point (picket) = 31 feature
- Magnetometry: 1 field component * 31 picket = 31 feature
- MTS: 2 field components * 1 frequency * 31 picket = 62 features

The output dimension of the problem was:

- 3 layers * 15 values of layer boundary depth = 45 parameters.

A total of 30 000 patterns were calculated.

3. Methodical statement of the problem

3.1 Datasets

The original data set was divided into training, validation, and test sets in a ratio of 70:20:10. Their dimensions were 21 000, 6 000, and 3 000 patterns, respectively.

The training of neural networks (NN) was performed on the training data set. The validation set was used to stop the training process (see Sect. 3.3). Independent evaluation of the results was performed on the test (out-of-sample) set.

3.2 Reducing dimensionality of the problem

In all cases, both in the field recovery problem and in the inversion problem, the so-called autonomous [8] determination was used, where a separate NN with one output was trained for each determined parameter.

Reduction of the input dimension of the problem was not carried out.

3.3 Use of neural networks

All networks used in this study, both for recovering and inversion, were used in the same way.

The type of NN used was the multilayer perceptron, which is a universal approximator. The architecture used had a single hidden layer with 32 neurons in it. Activation function was logistic in the hidden layer, and linear in the output layer. Training was carried out by the method of stochastic gradient descent.

To reduce the factor associated with the influence of the initialization of weights on the training of NN, 5 networks were used for each case under consideration, and the statistical indicators of their application were averaged.

To prevent overtraining, early stopping by validation dataset was used: training stopped after 500 epochs after minimum error on the validation set.

3.4 Integration of geophysical methods

When integrating geophysical methods, the data of two or three geophysical methods were simultaneously fed to the input of the NN. For individual use of data from the gravimetry and magnetometry methods, the NN input was fed by 31 features, for individual use of MTS data – 62 features, for simultaneous use of data from two geophysical methods – 62 or 93 features, for simultaneous use of data from all the three methods (only inversion) – 124 features.

3.5 Geophysical field components recovery

It was performed by direct application of neural networks. The values of known geophysical fields were fed to the network inputs, the corresponding values of the reconstructed field in a given picket were fed to the output.

3.6 Inverse problem

Here, the dependence of solution quality on the number of recovered values of geophysical field components was studied. For the considered geophysical method, the exact values of the geophysical field were randomly replaced by a given number of recovered ones. The goal was to determine the number of missing and recovered values for which the considered approach would give a positive result.

4. Results

4.1 Geophysical field components recovery

Results of geophysical components recovery are shown in Fig. 1 and Fig. 2. The serrated curves shape (Fig. 2) of dependences of the quality of the solution on the picket number is due to the location of some pickets on the boundaries of blocks with different thicknesses. There is a positive effect of data integration: the use of any two geophysical methods to recover the third shows a better result than using each method separately.

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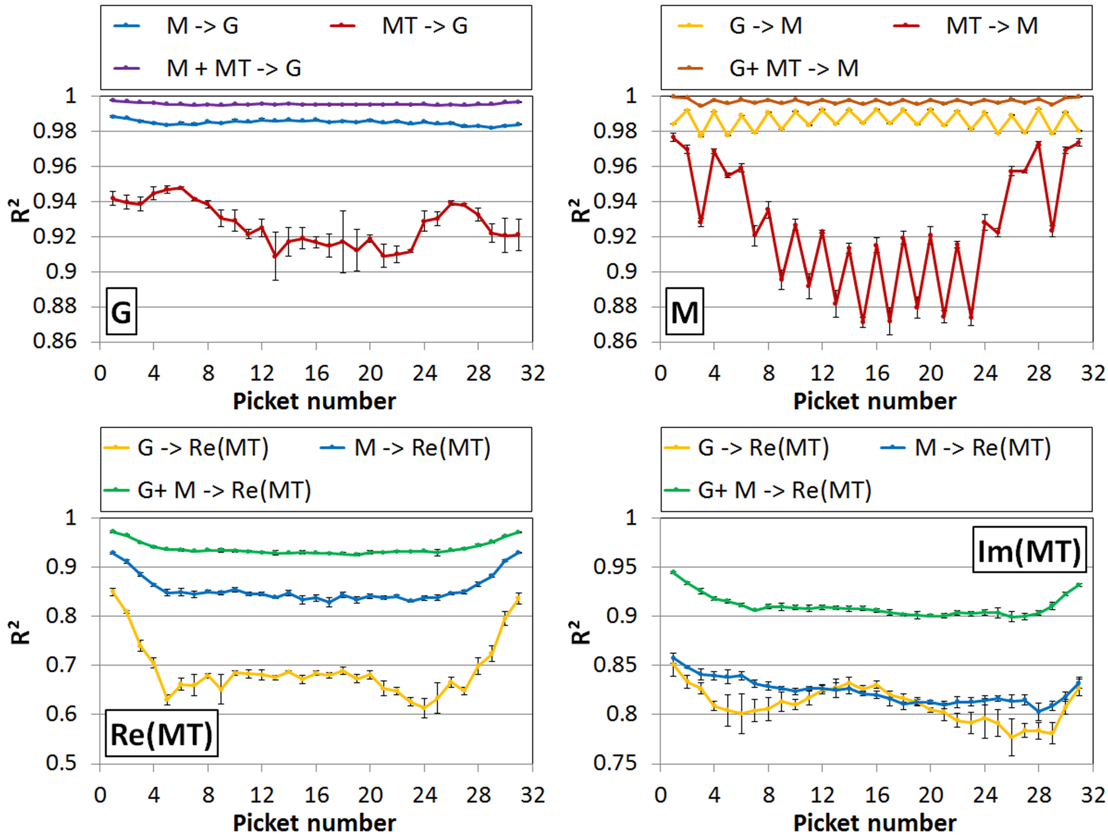

Figure 2: Quality (R^2) of recovery of geophysical field components.

4.2 Inverse problem solution

The results of the joint use of known and recovered data for solving the inverse problem are shown in Fig. 3. In most cases, this approach did not show a positive result: the use of only known data provides a better quality of the solution than the joint use of known data and data recovered from them. Only in some cases there is a segment where the application of the considered approach improves the result:

- For layer 1:
  - inversion on known magnetotelluric and recovered gravimetry data: G+MT(MT→G).
  - inversion on known magnetometry and magnetotelluric data and recovered gravimetry data G+M+MT(M+MT→G).
- For all layers:
  - inversion on known gravimetry and magnetotelluric data and recovered magnetometry data: G+M+MT(G+MT→M).

The presence of an extremum in the curves describing the dependence of the quality of the inversion on the number of recovered field values may be due to the fact that neural networks mainly pay attention not to concrete values, but to the shape of the fields curves.

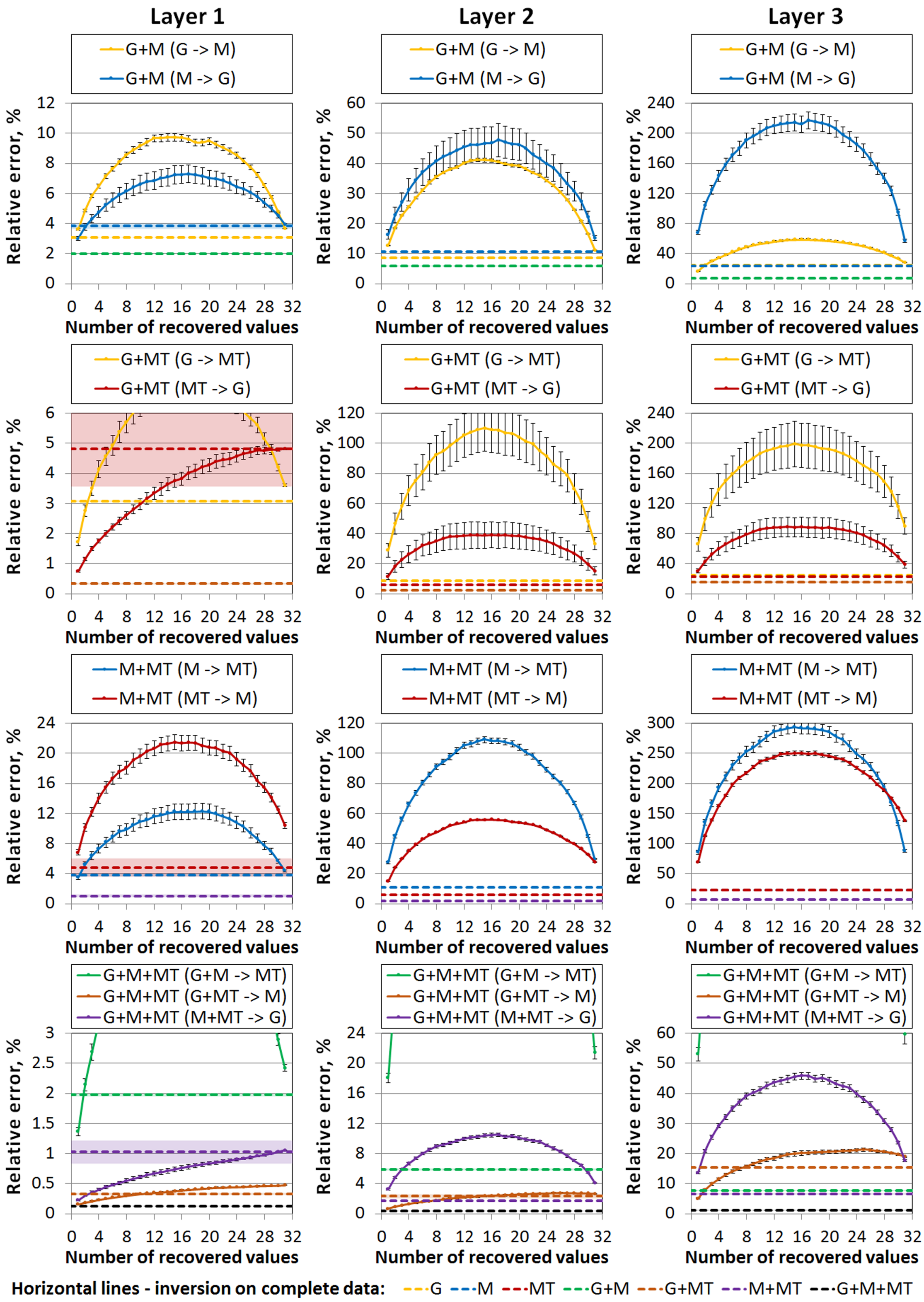

Figure 3: Dependence of the quality (relative error) of the solution of the inverse problem on the number of recovered values of geophysical field components. Horizontal lines – inversion on complete data, other lines – inversion with joint use of known and recovered data. The same color corresponds to the same complete known data.

5. Conclusion

Based on the results of this study, the following conclusions can be drawn:

- There is a positive effect of data integration in recovering fields components of one geophysical method by known data of other geophysical methods: the use of any two geophysical methods to recover the third one shows a better result than using each method separately.
- In some cases, an approach based on the reconstruction of one geophysical field from the data of other geophysical fields and their further joint application for inversion yields a positive result.

However, the considered approach did not show acceptable results and needs further improvement. As such an improvement, it is planned to use neural networks trained with noise addition, which are more resistant to distortions in the shape of geophysical fields curves.

Acknowledgments

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