[12] An automatic method for estimating the geomagnetic field

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Abstract

We introduce a new method for estimating the geomagnetic field. The method is based on a combination of a wavelet transform with radial basis neural networks. In the method, the recorded geomagnetic field variations are decomposed into different-scale components and the degree of disturbance of each component is estimated, enabling the conclusion about the field state. For the verification of the method, we used geomagnetic data from the "Paratunka" station (Paratunka, Kamchatka region, data registration is carried out by IKIR FEB RAS). Analysis of the spectral-temporal characteristics of geomagnetic field variations during periods of moderate and strong magnetic storms was performed. Weak perturbations were detected in the geomagnetic field before the storms. The obtained results have confirmed the effectiveness of the proposed method.

Keywords: neural networks, wavelet transform, geomagnetic data, Earth's magnetic field

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Introduction

The work aims to create theoretical and software means of analysis of geomagnetic field parameters and perturbation selection in the period of high solar activity. It is known that the study of Earth's magnetic field variations is the basis for evaluation of properties and state of electromagnetic fields in the near-Earth space [1]. As a result of the impact of solar activity on the near-Earth space magnetospheric perturbations of various scale and duration occur, which negatively impact on modern technological systems [1, 2]. The magnetic field may also exhibit natural catastrophic events or processes at their preparation stage [2].

Observations of the magnetic field are carried out in more than 70 countries. Traditionally ground magnetometers are used for this. Especially important are observation in high-latitude regions, and space weather forecast is required for reliable operation of technical infrastructure in the Arctic region. The recorded variations of geomagnetic field have a complex non-stationary structure. Fig. 1, as an example, shows horizontal components of geomagnetic field in the quiet period and during a magnetic storm. At night time geomagnetic activity increases, and sharp emissions and vibrations may occur during magnetic storms [1, 3, 4]. In addition to the daily course, geomagnetic data have seasonal, secular course and are subject to the 11-year cycle of solar activity [1].

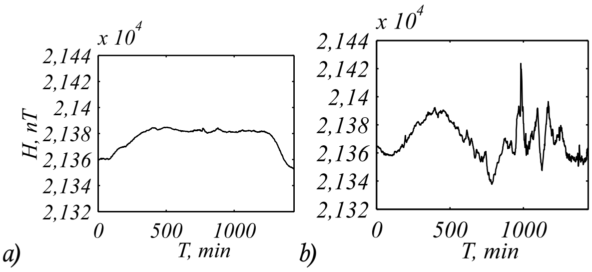

Fig. 1. H-components of the magnetic field of the Earth: a) quiet diurnal variation; b) perturbed diurnal variation

The complex structure of geomagnetic field variations considerably complicates the process of their studying, and classical data analysis methods become of little effect to solve the task set [1, 4-6], for they do not allow to identify certain regularities and lead to loss of important information. The disadvantage of use of classical methods and approaches is also their insufficient degree of automation, which is very important for the tasks of rapid processing of near-Earth space data and of space weather forecast.

As shown by recent studies [4, 7-17], the natural and the most effective way of describing such data are non-linear adaptive approximating schemes. Based on this approach, empirical mode decomposition methods (EMD) [16, 17] and adaptive wavelet decompositions [4, 8-15] are currently receiving intensive development in processing and analysis of complex data structures [4, 8-15]. Both of these methods take into account the particular structure of the signal and make it possible to describe the processes with complex structure [18, 19]. The advantage of wavelet analysis is a large number of orthogonal bases with compact support and the availability of fast computational algorithms [19]. The main difficulty in its use is the non-obvious choice of the basis for a specific task solution [19-21]. At the same time, for function approximation tasks there are proposed criteria for selection of wavelet basis and constructed computational algorithms which allow to pick basis adaptively and to minimize the error of approximation obtained [19, 21]. Unlike wavelet transform in the EMD-method basis functions are determined directly from the data, and the constructed basis is a posteriori [20, 22]. Therefore, in most cases extracted approximating components can be effectively used only for processing of the signal from which they were extracted. Such a basis is an empirical, and for approximation of the geomagnetic field variations with a continuously changing structure it is not effective enough. The disadvantage of EMD is also not fully developed theoretical basis [18, 20]. In particular, the linear independence of approximating components is not mathematically proven, and the orthogonal property of selected empirical modes can only be checked a posteriori [23]. In turn, wavelet analysis has a well developed mathematical apparatus and is becoming widespread in the field of geophysics. Based on the wavelet transformation the methods are proposed for the analysis of features that occur in the geomagnetic field during periods of strong solar flares [24, 25], the algorithms are developed that automatically detect periods of the initial phase of the storm [26] and algorithms for noise removal and elimination of the periodic component caused by rotation of the Earth [27, 28]. In this paper wavelet analysis was used in conjunction with neural networks. The neural networks apparatus is widely used in images recognition tasks and data analysis [29-31]. Neural networks also are effective in the field of geophysics [14, 32, 33]. This apparatus allows to reproduce complex nonlinear dependence of data [32-34], to reveal hidden patterns in the data, and is easy to be implemented in automatic mode [35, 36].

The basis of the method developed by the authors is multiresolution wavelet decomposition (MWD) [19] and radial neural networks [36]. In the work on the basis of MWD variations of the geomagnetic field are decomposed on different scale components that characterize the field perturbed, and the noise is suppressed. Selected components enter the radial neural networks that perform assessment of their disturbance degree. A detailed study of geomagnetic data structure (on the example of the horizontal component of Earth's magnetic field (H-component)) performed on the basis of MWD made it possible to identify signs of field perturbations and on their basis to generate images of the classes for the radial layers of neural networks. This improved the quality of the task solution on the basis of neural networks and, in contrast to the traditional architecture, has allowed to significantly reduce the number of used examples in their radial layer.

To solve the problem six radial neural networks, united in electronic expert team, were formed in this paper. Formation of conclusion on the state of the geomagnetic field is carried out on the basis of a decision rule that uses combinations of the decisions of experts team.

Geomagnetic data of the Paratunka station (Paratunka village, Kamchatka region, Institute of Cosmophysical Research and Radio Wave Propagation of FEB RAS performs registration) for the period 2002-2008 were used to test the method. The executed analysis of data in high geomagnetic activity periods has shown the prospects of application of the developed method and the possibility of its use in tasks of forecasting space weather and strong magnetic storms predictions.

Description of the method
Decomposition of the geomagnetic field variations at different scale components

As a basic space of recorded discrete data $f_0(t)$ is considered an enclosed space with a resolution $j=0$: $V_0 = clos_{L^2(R)}(2^0\phi(2^0 t-k) \ : k \in Z)$, generated by the scaling function $\phi \in L^2(R)$ [19]. Basing on multiresolution wavelet decomposition to a level m you can present data as a sum of approximating and detailing components:

$$f_0(t) = \sum_{j=-1}^{-m} g\left[2^j t\right] + f\left[2^{-m} t\right], \tag{1}$$

where $g\left[2^j t\right] \in W_j$, W_j – is a space with resolution j, generated by the wavelet basis $\Psi_{j,n}(t) = 2^{j/2}\Psi(2^j t - n)$, detailing *various scale components* $g\left[2^j t\right] = \sum_n d_{j,n}\Psi_{j,n}(t)$ $d_{j,n} = \left\langle f, \Psi_{j,n}\right\rangle$, j – scale; *approximating component* $f\left[2^{-m} t\right] = \sum_k c_{-m,k}\phi_{-m,k}(t)$, $c_{-m,k} = \left\langle f, \phi_{-m,k}\right\rangle$.

In this paper we used wavelets $\Psi_{j,n}(t)$ and scaling function $\phi_{-m,k}(t)$ Daubechies order 3.

Data representation diagram based on the base of (1) is shown in Fig. 2.

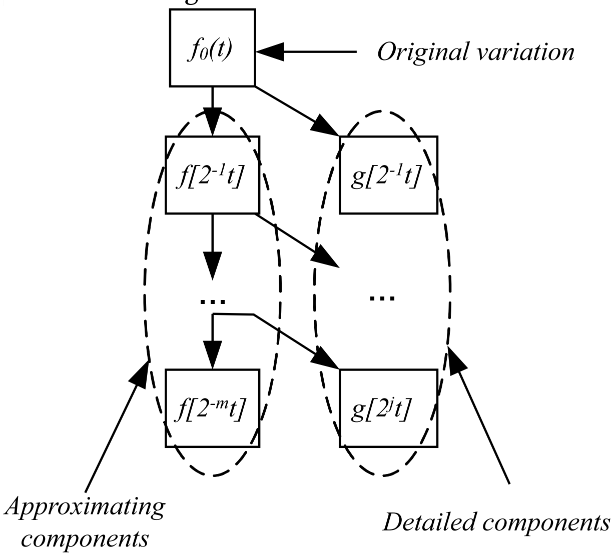

Fig. 2. The scheme of data decomposition to the level of m

Introduction of classes of the geomagnetic field states and defining their attributes

A characteristic of the magnetic field state is the index of geomagnetic activity K [1]. The paper considers three possible geomagnetic field conditions, and there were accepted: 1) "quiet" condition (class 1), if the total sum of the daily index of geomagnetic activity is $\sum K \le 10$;
2) "weakly disturbed" condition (class 2), if the $10 < \sum K \le 18$;
3)"disturbed" condition (class 3), if $\sum K > 18$.
A detailed study of geomagnetic data structure showed [4, 14, 15, 37, 38] that coefficients $d_{j,n}$ of the detailing components $g[2^j t]$ of the scales $j = -1,-2,...,-6$ characterize disturbance of the field, and in the periods of increased geomagnetic activity their absolute values significantly increase. Fig. 3, as an example, shows detailing components of geomagnetic field variations of scale $j = -4$ in the periods of "quiet" and " disturbed" field states. Following these results, the absolute values of the component coefficients $|d_{j,n}|$ will be taken as *a measure of their geomagnetic disturbance*. As a *measure of geomagnetic disturbance* of $g[2^j t]$ *component* a maximum of the absolute values of its coefficients will be taken: $V_{g_j} = \max_n |d_{j,n}|$.
In accordance with considered field states let us assume that the component $g[2^j t]$ can have one of the three possible states: "quiet", "weakly disturbed", or "disturbed". As shown above, the state of the components $g[2^j t]$, $j = -1,-2,...,-6$ defines the state of the geomagnetic field. In order to assess its condition let us introduce the following *decision rule*:

1) if all the components have a «quiet» state, or only one of the components has a «weakly disturbed» state, the geomagnetic field has a «quiet» state (class 1);
2) if at least one of the components has a "disturbed" state, the geomagnetic field has a "disturbed" state (class 3);
3) in other cases it is considered that the field has a "weakly disturbed" state (class 2).

Assessment of each of the 6 selected components state will be performed on the basis of radial neural networks, whose forming method is described below.

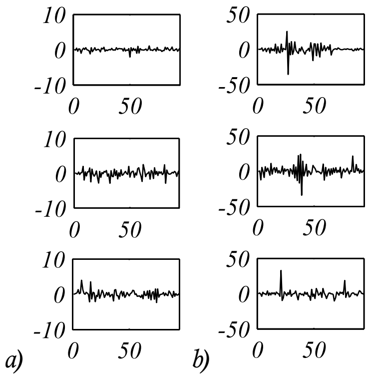

Fig. 3. Detailing components of geomagnetic field variations of scale j = -4, obtained using Daubechies wavelet of order 3:
a) - periods of «quiet» state of the field,
b) - periods of «disturbed» state of the field.

Forming a radial layer of the neural network

Radial neural networks traditionally have three layers [36]: the input layer; hidden layer of examples (radial layer) containing signs of classes; linear output layer, defining if input image belongs to the class.
In the radial layer the following conversion of input data is performed [36]:
1. Assessment of the state of neurons based on weighing function $r = \|p - w\| b$, where p is the entry vector, w is example vector, and b is bias.
2. Using a threshold activation function, evaluation proximity measure of the input vector and example. When the r distance between the p input vector and the w examples vector is reduced, the output of activation function approaches the value "1", otherwise – to the value "0".
In accordance with the set task, the input vector of the neural network is the $g[2^j t]$ component. The task of the neural network is estimating of its condition. The measure of geomagnetic perturbation of $g[2^j t]$ component is the above mentioned value $V_{g_j} = \max_n |d_{j,n}|$.
Presented in Fig.4, values of $V_{g_{-2}}$ and $V_{g_{-6}}$, determined for components in periods of "quiet", "weakly

disturbed" and "disturbed " field conditions indicate that the ranges of their values have significant overlap. This is due to complex nature of the process and the lack of clear boundaries between the considered classes. Given these characteristics of the process, let us introduce the following *subclasses of the component states*:

1) for a "quiet" state – a subclass « α – quiet» (k_1): $\max_n |d_{j,n}| \le T_j^{\alpha_1}$ and « β – quiet» (k_2): $T_j^{\alpha_1} < \max_n |d_{j,n}| \le T_j^{\beta_1}$.

2) for "weakly disturbed " state – a subclass « α -weakly disturbed » (k_3): $T_j^{\beta_1} < \max_n |d_{j,n}| \le T_j^{\alpha_2}$ and « β -weakly disturbed » (k_4): $T_j^{\alpha_2} < \max_n |d_{j,n}| \le T_j^{\beta_2}$.

3) for "disturbed " state – a subclass « α -disturbed» (k_5): $T_j^{\beta_2} < \max_n |d_{j,n}| \le T_j^{\alpha_3}$ and « β -disturbed» (k_6): $\max_n |d_{j,n}| > T_j^{\alpha_3}$.

When training the neural network the thresholds $T_j^{\alpha_1}, T_j^{\beta_1}, T_j^{\alpha_2}, T_j^{\beta_2}, T_j^{\alpha_3}$, determining the input feature membership to a subclass, can be estimated by minimizing network error on a set of training vectors.

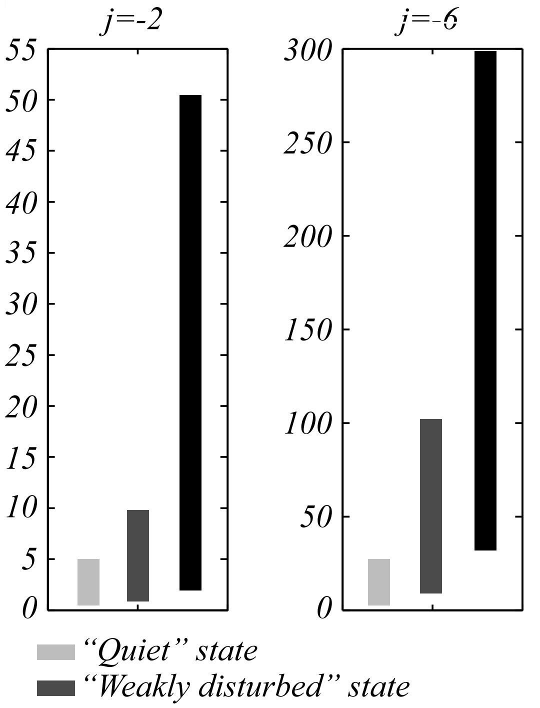

Fig.4 The values of $V_{g_{-2}}$ and $V_{g_{-6}}$, defined for the components in the periods of "quiet", 'weakly disturbed" , and "disturbed" states of the field (100"quiet", 190 "weakly disturbed",and 86 "disturbed" field variations were used in estimation).

The introduced above measures of geomagnetic disturbance define characteristics of considered subclasses. Using disturbance measure of the coefficient, its absolute value $|d_{j,n}|$, for each introduced subclass k_i let us create one example P_{j,k_i} in the radial layer of the neural network *according to the rule*:

$$P_{j,k_i} = \frac{\sum_{u_i=1}^{U_i} D_{j,u_i}}{U_i}, \qquad (2)$$

where $D_{j,u_i} = \left(|d_{j,1}^{u_i}|, |d_{j,2}^{u_i}|, \ldots, |d_{j,N_j}^{u_i}| \right)$, u_i – the number of the component of subclass k_i, N_j – the length of the component of the scale j, U_i – quantity of the components of the subclass k_i.

Applying the rule (2) in the formation of radial layer of the neural network, in contrast to the traditional approach [36], can significantly reduce the number of examples used and optimizes network performance. Obtained according to the rule (2) examples of subclasses $P_{j,i}$ for the scale $j = -6$ are shown at Fig. 5. Analysis of the Fig. 5 shows that separation of images is the best at night, due to the nature of the geomagnetic process and increase of disturbances in times of storms at night.

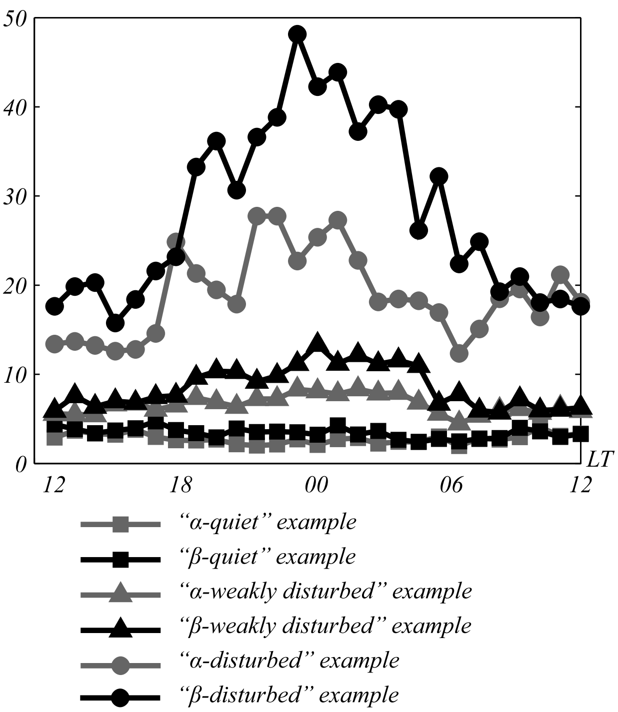

Fig. 5 Examples of subclasses of the radial layer of the neural network for the scale $j = -6$.

Fig. 6 shows the architecture of the neural network obtained.

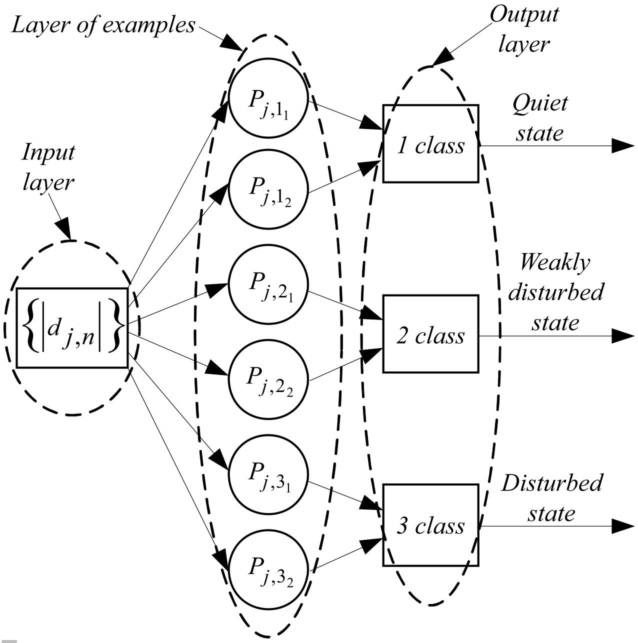

Fig. 6 Architecture of the neural network

Designed *structure of the neural network team that performs evaluation of the geomagnetic field state* is shown in Fig.7. The team consists of six radial neural networks, each of which performs assessment of the state of a specific detailing component of variation of the geomagnetic field. Formation of conclusion on the state of the geomagnetic field is based on decisions of the team neural networks and is performed using the entered above *decision rule*.

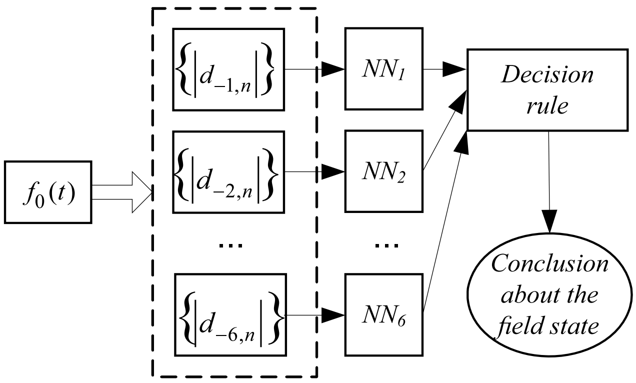

Fig.7 The structure of the neural network team.

Evaluating the effectiveness of the method

With the help of the constructed neural networks team assessment was performed of the geomagnetic field variations state, obtained at the Paratunka station (Kamchatka Region) for the period 2002-2008. The results of the team work are presented in Table 1. To evaluate the effectiveness of the proposed method a comparison of the gained results was made with the working results of conventional radial neural network, which is fed to the input with the original variation of the geomagnetic field (without the use of wavelet transform). Exemplary images of radial layer of such a network, in accordance with the procedure (2) were created as follows:

$$P_{k_i} = \frac{\sum_{u_i=1}^{U_i} f_{0,u_i}}{U_i}$$

where f_{0,u_i} is the original variation of the subclass k_i, u_i is the number of variation of the subclass k_i, U_i is the quantity of variations of the subclass k_i.

The working results of the traditional neural network, presented in Table 1 (right column), confirm the effectiveness of the proposed method and the possibility of its use to automatically determine the perturbations extent of recorded geomagnetic field variations.

Table 1. Accuracy of operation of neural networks

Analyzed period	Error of network collective, %	Error of traditional network, %
2002	18,58	48,82
2003	11,96	71,4
2004	19,89	51,16
2005	18,39	54,52
2006	18,57	55,7
2007	23,01	60
2008	18,85	54,37

Analysis of work of the developed team of neural networks in the periods of high geomagnetic activity showed that in more than 70% of events on the eve of strong and moderate magnetic storms weak perturbations of the geomagnetic field are recorded (97 events have been analyzed). Fig. 8, 9, as an example, show results of the team work in times of two events: a magnetic storm with a sudden beginning on 2 October, 2013, and a magnetic storm with a gradual beginning on April 20, 2005. For two days before the start of the first magnetic storm, 29 September, at the Sun occurred proton C1.2 class flare with duration of 200 minutes, whose maximum was observed at 23:39 UT. The solar wind speed increased gradually on 1 October from 250 to 400 km / sec., a gradual onset of the storm at 07.48 UT have been registered in the high latitudes[39]. The upper part of Fig. 8 shows the values of the indices of geomagnetic activity K (K-index), below the variations are shown of the geomagnetic field (H-components). The bottom of Fig. 8 shows the results of evaluation of the geomagnetic field variations with the help of built team. It is seen that on the eve of the magnetic storm on October 1 collective of neural networks recorded weak perturbations. At the analyzed mid-latitudes the sudden onset of magnetic storm was registered on 2 October at about 01:52 UT [39].

Gradual start of the second analyzed magnetic storm was registered at mid-latitudes on 20 April, at about 03:00 UT. The solar wind speed from the beginning of the day increased from 380 to 540 m / s. As the analysis of Fig. 9 shows, two days before the event the team of neural networks recorded weak perturbations of the geomagnetic field.

Results obtained are consistent with the results of [13, 14] and are important for condition forecast of near-Earth space and for prediction of strong magnetic storms.

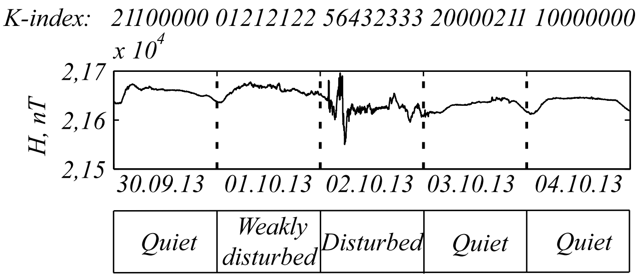

Fig. 8. The results of evaluation of condition of variations of the geomagnetic field during the period 30.09.2013-04.10.2013 years.

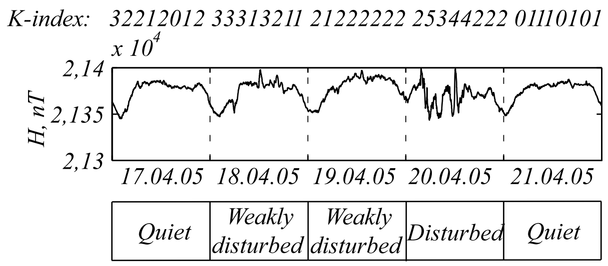

Fig. 9. The results of evaluation of condition of variations of the geomagnetic field during the period 17.04.2005-21.04.2005 years.

A detailed analysis of the spectral-temporal characteristics of field variations during magnetic storms showed that in most cases geomagnetic disturbances fall in various detailing components. Fig. 10, 12 show trees of wavelet decomposition of the geomagnetic field variations for magnetic storms under consideration, gray colour marks the components that have been identified by neural networks as "disturbed". It is evident that in the first case the geomagnetic disturbances are recorded in all components, which indicates the complex spectrum of variations and multiscale nature of the process. In the second case deviations are recorded in detailing components of 3 – 6 th scale. Also, in Fig. 10, 12 are shown the original variations of the geomagnetic field and their disturbed constituents, obtained by restoring "disturbed" detailing components. Built wavelet spectra of perturbed components of field variations, shown in Fig. 11, 13, confirm a complex multiscale nature of the analyzed processes.

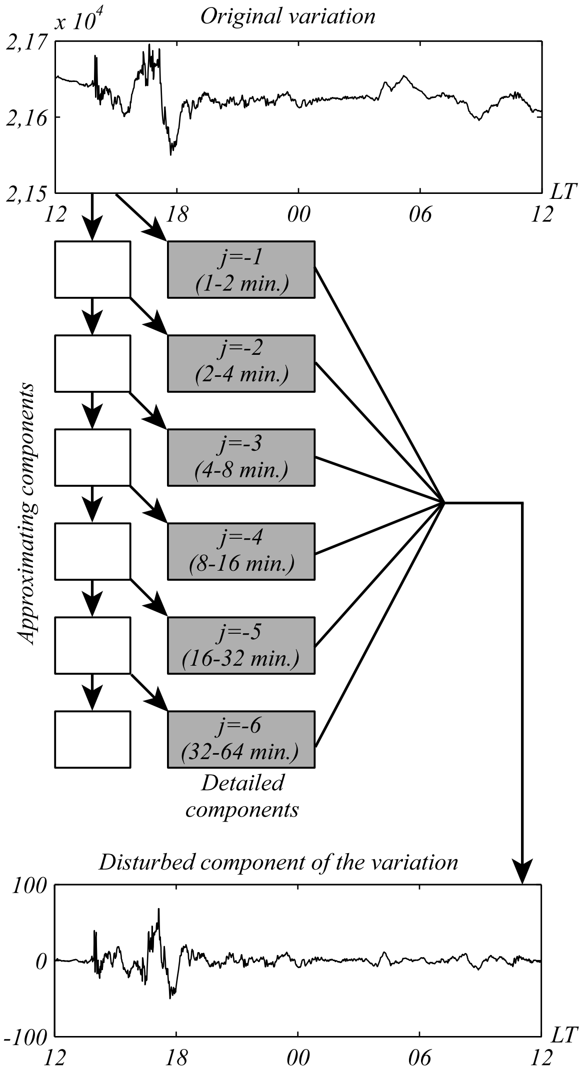

Fig. 10. Variation of the geomagnetic field during magnetic storm 2 October 2013 and its disturbed component.

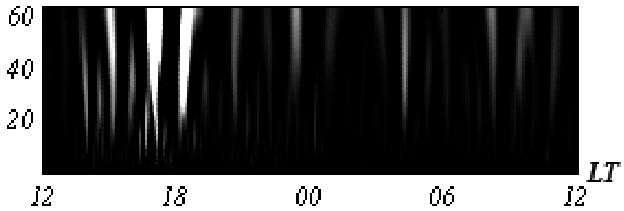

Fig. 11. The wavelet spectrum of the disturbed component of the geomagnetic field variation during the magnetic storm, 2 October 2013.

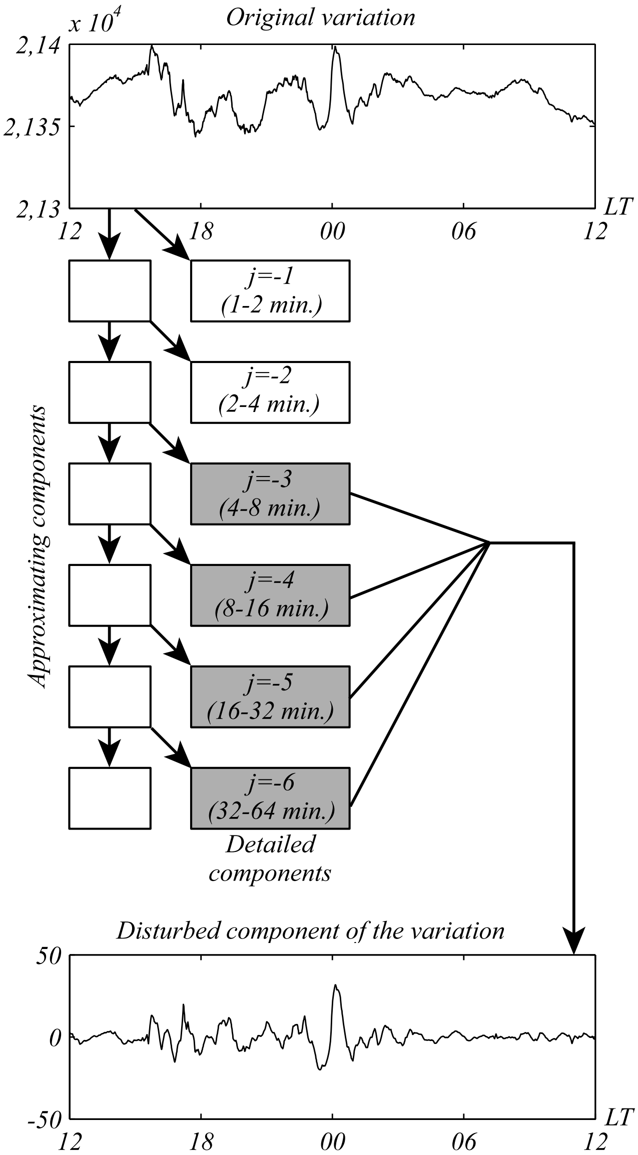

Fig. 12. Variation of the geomagnetic field during the magnetic storm 20 April, 2005. and its disturbed component.

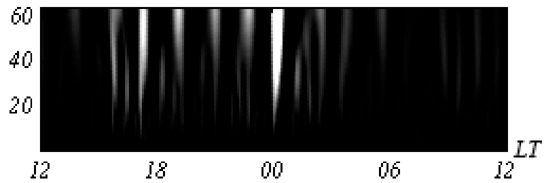

Fig. 13. The wavelet spectrum of the disturbed component of the geomagnetic field variation during the magnetic storm 20 April, 2005.

Conclusion

The paper describes an automatic method for assessing the state of the geomagnetic field, based on a combination of wavelet transform with radial neural networks. Analysis of the constructed neural networks team work has confirmed the effectiveness of the proposed method. The study of spectral-temporal characteristics of magnetic storms (86 events analyzed) showed that disturbances arising in the geomagnetic field in the majority have a complex spectral structure and appear in various components of the field variations. It is noticed that on the eve of storms the proposed method recorded weak perturbations of the geomagnetic field, which is important for forecasting the state of near-Earth space and predicting strong magnetic storms.

In the experiments the variations of the geomagnetic field were used that had been obtained at Paratunka station in the Kamchatka region (data logging performed by Institute of Cosmophysical Research and Radio Wave Propagation of FEB RAS).

Acknowledgement

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