Method of ionospheric data analysis based on a combination of wavelet transform and neural networks

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Abstract

The paper presents a hybrid system based on a combination of wavelet filtering operations and regression neural networks. The system is adapted to analyze the ionosphere data obtained at "Paratunka" station (Kamchatka). Testing of the system has shown its efficiency in the tasks of analysis of characteristic properties of ionospheric data and detection of anomalies occurring during disturbed periods. For a detailed analysis of anomalies, computing solutions based on the application of continuous wavelet transform and threshold functions were suggested. The developed computational tools were implemented in software environment (http://aurorasa.ikir.ru:8580).The research was supported by RSF Grant №14-11-00194.

Keywords: wavelet-transform; neural networks; critical frequency of the ionosphere; ionospheric storms; anomalies; magnetic storms

1. Introduction

The paper is aimed at the creation of theoretical and software means for analysis of ionospheric parameters and detection of disturbances during increased solar activity and geomagnetic storms. Ionosphere is considered to be a region of the atmosphere which begins at the altitude of about 60 km and stretches to the altitude of 1000 km and higher [1-4]. Propagation of the significant part of radio wave spectrum is determined by the ionosphere and investigation of ionospheric characteristics allows us to use it as an indicator of the processes occurring in the upper atmosphere. The main sources of ionization of the ionosphere are the Sun ultraviolet and X-ray radiation, solar wind flux particles reaching the altitudes of the ionosphere through the magnetosphere in a complicated way, cosmic rays and meteors [1]. Ionospheric parameters considerably change with altitude. They depend on solar activity cycle, geomagnetic conditions, geographic coordinates and contain characteristic diurnal and seasonal changes [3-7]. One of the important tasks of ionospheric parameter analysis is the monitoring of ionospheric state and detection of anomalies [3-8] which have negative impact on satellite system operation and propagation of radio communication. At present, the technologies of observation of the near Earth space and data analysis methods are being intensively developed. However, the capabilities of analysis and forecast of ionospheric state are still quite limited. Of important scientific and applied significance are the empiric methods and technical means of detection and identification of anomalous behavior of the ionosphere [7, 9].

Ionospheric data have a complicated structure and disturbing factors of different nature make the direct application of traditional methods of time series analysis ineffective [10, 11]. For the moment, the most developed empirical model of the ionosphere is the International reference IRI model [9, 12], which is based on a wide range of ground and space data. The quality of its estimates is significantly affected by the presence of recorded data in a definite region [9]. New developments of empirical models applying the methods of pattern recognition and neural networks (NN) [3, 8] allow us to improve the quality of forecast in comparison to IRI model. They are implemented easily in automatic mode and are quite flexible. The disadvantage of such models is their strong dependence on input data, their integrity and relatively low level of noise. Recent investigations show that representation of ionospheric parameters on the basis of nonlinear adaptive approximating schemes [2, 13-17] is natural and the most effective for their pre-processing and independent analysis. The methods of decomposition into empirical modes [16, 17] and adaptive wavelet decompositions [2, 13-15] based on this approach are intensively developing at present.

Based on a complex approach applying multiresolution wavelet analysis (MRA) and neural networks, the authors of the paper modeled a characteristic variation of the ionospheric process. During magnetic storms, anomalous disturbances in foF2 were detected which were reflected in the modeling results. Application of MRA to detect a smoothed (trend) component of foF2 time series allowed us to improve the quality of solution of the problem based on neural networks. Methods of continuous wavelet transform and threshold functions were used for the detailed analysis. Tests were carried out on the data of ionospheric F2 layer critical frequency (foF2). The data were obtained at «Paratunka» site (Paratunka, Kamchatskiy kray, IKIR FEB RAS).

2. Description of the method

2.1. Data decomposition based on MRA

In the function of the reference space of initial data $f_0(t)$ we consider a closed space with resolution $j=0$: $V_0 = clos_{L^2(R)}(2^0\phi(2^0 t-k)) : k \in Z)$, generated by a scaling function $\phi \in L^2(R)$ [18]. Based on the MRA, the time series

$f_0(t)$ is represented in the form of linear combination of different-scale components, smoothed one $f\left[2^{-m}t\right]$ of scale m and detailing ones $g\left[2^{j}t\right]$ of scales $j=\overline{-1,-m}$ [18]:

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

where different-scale detailing components $g\left[2^{j}t\right]=\sum_k d_{j,k}\Psi_{j,k}(t)$, $d_{j,k}=\left\langle f,\Psi_{j,k}\right\rangle$, Ψ is the basic wavelet, j is resolution; *approximating component* $f\left[2^{-m}t\right]=\sum_k c_{-m,k}\phi_{-m,k}(t)$, $c_{-m,k}=\left\langle f,\phi_{-m,k}\right\rangle$, ϕ is a smoothing scaling function. The inferior index 0 corresponds to the initial resolution of the data.

Scheme of data representation based on function (1) is shown in Fig. 1.

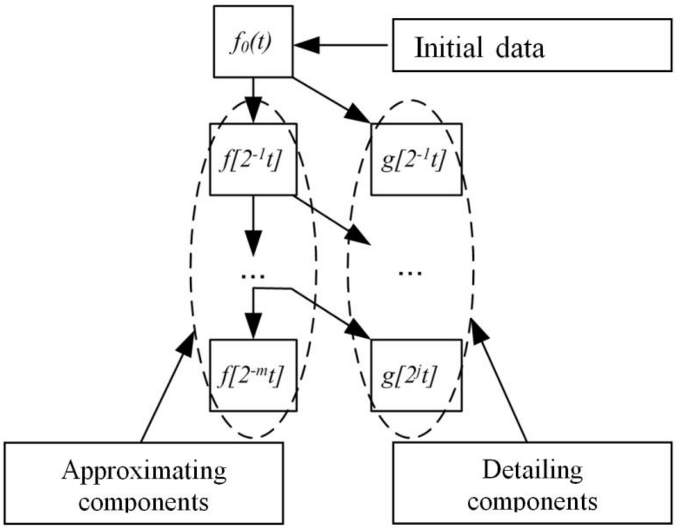

Fig. 1. Scheme of data decomposition to level m.

We applied the following wavelet selection criteria, that were suggested in the paper [19] for the first time:

1. Number of zero times.

The number of zero times p characterizes the ability of a wavelet to discover a feature of the kind $\alpha \leq p$, where α is Lipschitz uniform condition [20].

2. Carrier size.

Wavelet transform generates artificial «jumps» at the ends of function f, reflecting in decomposition coefficients. Neighborhood sized on the scale $-m$, containing a tip effect, depend on the carrier size of a wavelet q and equals $2^{-m} * q$. In the paper to exclude the tip effect, we used the function mirror image ($2^{-m} * q$ of values was added at the ends).

3. Wavelet smoothness.

Just like the number of zero times, wavelet function smoothness characterizes its ability to discover a feature of the kind $\alpha \leq p$ [20].

Thus, to select a wavelet, it is necessary to choose between the number of zero times and carrier size. For orthogonal wavelets, Daubechies proved in the paper [20] that if a wavelet Ψ has p zero times, its least carrier equals $2p-1$. It was also proved in the paper [20] that orthogonal wavelets of Daubechies class is the only family of basic wavelet functions which have a minimal size of a carrier for the defined number of zero times.

In the majority of applied problems, it is necessary that approximating components allow us to obtain the best approximation of a function. The best approximation of a function f in approximating components is provided by a scaling function ϕ [20] with enough number of zero times p. Thus, it is important in this case that zero times have not only a wavelet Ψ but ϕ. Orthogonal basis family satisfying this requirement and having the carriers of the least size is a Coiflet [20]. A Coiflet has a carrier of the size $3p-1$ instead $2p-1$ for Daubechies wavelet.

2.2. Construction of a neural network model

Approximating component $f\left[2^{-m}t\right]$ (see the relation (1)) is used to identify a neural network model on the basis of following operations:

1. We make wavelet recovery of the obtained component $f[2^{-m}t]$ to the initial resolution, remove additional mirror parts and obtain its representation as follows: $f_0(t)=\sum_k c_{0,k}\phi_{0,k}(t)$.

2. We divide the obtained vector of coefficients $\{c_{0,k}\}_{k=1}^{K}$, where K is the vector length, into blocks $\{c_{0,k}\}_{k=1}^{S}, \{c_{0,k}\}_{k=2}^{S+1}, \ldots, \{c_{0,k}\}_{k=K-S}^{K}$. A block length is $S = 24$ (determined according to diurnal variation of hourly data of foF2).

3. Applying the obtained blocks we form a neural network of changeable structure [21]. The criteria of quality of network training is $E_A = \left(\frac{1}{R}\sqrt{\sum_{r=1}^{R} e_{A,r}^{\,2}(l)}\right) < \varepsilon_A$, where $\varepsilon_A > 0$ is a prescribed small value, $e_{A,r}(l) = \hat{c}_{0,l}^{r} - c_{0,l}^{r}$ is an error of the solutions at a discrete time point l with advance time r, $c_{0,l}^{r}$ is the desirable, $\hat{c}_{0,l}^{r}$ is the real output value of network, R is the length of network output vector.

The formed neural network displays data $y: f_0(\cdot) \rightarrow f_0^*(\cdot)$, where $f_0(\cdot)$ is a NN input, $f_0^*(\cdot)$ is a NN output. When function $f_0(\cdot)$ values from some interval $(l-Q, l)$ are input to a trained NN, the network calculates its advance values on a time interval $(l+1, l+I)$ where l is the current time point; I is the length of advance interval. NN error is determined as a difference between the desirable $f_0^*(\cdot)$ and real $\hat{f}_0^*(\cdot)$ output values of the function $e(t) = \hat{f}_0^*(t) - f_0^*(t)$.

A trained neural network allows us to recover data typical time variation. Thus, detection of anomalous changes may be based on the analysis of neural network errors $e(t)$.

2.3. Detection of anomalous changes based on continuous wavelet transform and threshold functions

To detect different-scale anomalous changes, we used computational solutions based on continuous wavelet transform $(W_\Psi f)(b,a) := |a|^{-1/2} \int_{-\infty}^{\infty} f(t)\Psi\left(\frac{t-b}{a}\right)dt$, Ψ is a wavelet, $f \in L^2(R), a, b \in R$, $a \neq 0$, and application of a threshold function

$$P_{T_a}(W_\Psi f_{b,a}) = \begin{cases} W_\Psi f_{b,a}, if \left|W_\Psi f_{b,a} - W_\Psi f_{b,a}^{med}\right| \geq T_a \\ 0, if \left|W_\Psi f_{b,a} - W_\Psi f_{b,a}^{med}\right| < T_a \end{cases}, \tag{2}$$

where the threshold $T_a = U * St_a$ determines the presence of an anomaly on a scale a near a point ξ, which is contained in a carrier $\Psi_{b,a}$, U is a threshold coefficient, $St_a = \sqrt{\frac{1}{\Phi - 1}\sum_{u=1}^{\Phi}\left(W_\Psi f_{b,a} - \overline{W_\Psi f_{b,a}}\right)^2}$, $\overline{W_\Psi f_{b,a}}$ and $W_\Psi f_{b,a}^{med}$ are an average value and a median determined in a moving time window of the length Φ. According to (2) the threshold coefficient U determines the presence or absence of anomalous changes in the data under analysis. To minimize the error, a posteriori risk which was minimized was used in the estimates of the coefficient U.

Anomaly intensity at the time point $t = b$ was calculated as

$$I_b = \sum_a \frac{P_{T_a}(W_\Psi f_{b,a})}{\left\|W_\Psi f_{b,a}\right\|_2}, \tag{3}$$

where $\left\|W_\Psi f_{b,a}\right\|_2 = \sqrt{\sum_{N_a}\left(P_{T_a}(W_\Psi f_{b,a})\right)^2}$, N_a is the series length on a scale a.

Fig. 2 illustrates an example of detection of ionospheric data anomalies and the possibility of estimation of their parameters.

3. Results of application of a method for ionospheric data analysis and detection of anomalies

3.1. Construction of neural network models

To construct neural network models, ionospheric critical frequency data of "Paratunka" site (Kamchatskiy kray, IKIR FEB RAS) for 1968-2010 were used. The dependence of ionospheric parameter time variations on season and the level of solar activity was taken into consideration in the modeling (solar activity was estimated by radio radiation at the wavelength of f10.7; if f10.7<100, the activity was considered to be low, in other case the activity was considered to be high). Separate models were constructed for winter and summer seasons and for high and low solar activity. To construct the models of reproduction of typical ionospheric parameters, the data for the periods without strong magnetic disturbances and seismic activity in Kamchatka were used to train neural networks (earthquakes with the energy class of $Ks \geq 12$ which occurred within the radius of 300 km from the site of ionospheric sounding). The data which had significant gaps were not used in the training of the neural network.

According to the results of paper [22], we determined the level of decomposition $m = 3$ and obtained the representation of ionospheric parameter time series in the following form (see relation (1)): $f\left[2^{-3}t\right] = \sum_k c_{-3,k}\phi_{-3,k}(t)$

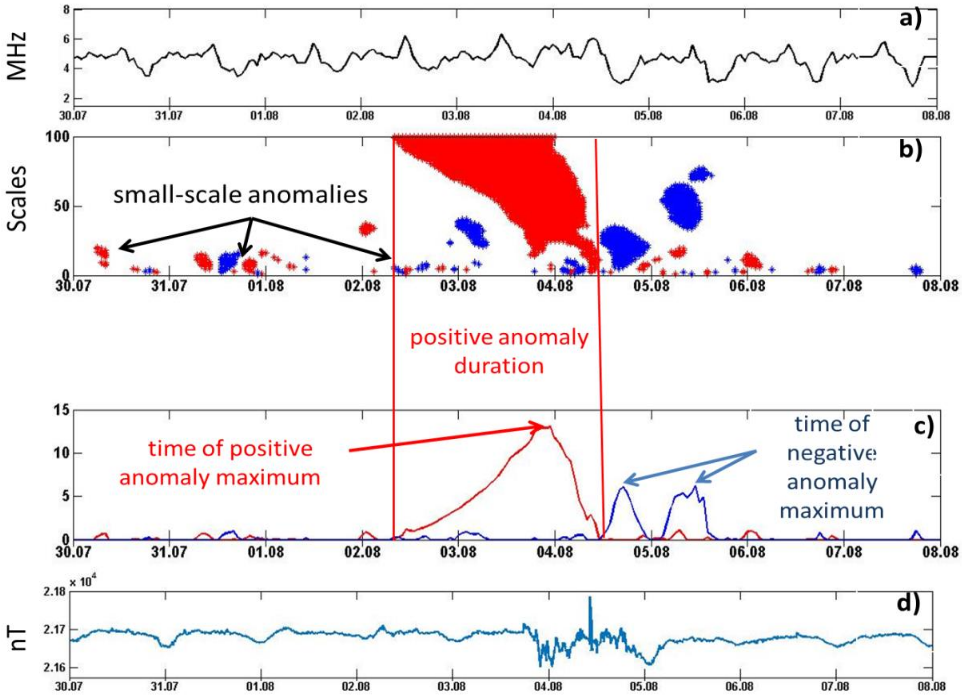

Fig. 2. Processing results of foF2 for 30.07 – 07.08, 2010 a) –foF2 data; b) – ionospheric anomalies (determined by relation (2), red– positive anomalies; blue – negative anomalies); c) – intensity of ionospheric anomalies (estimated by relation (3)); d) – H-component of the Earth magnetic field characterizes geomagnetic field state.

Input vector dimension was determined taking into account diurnal variation of foF2 data and was accepted to be equal to 24 counts. The structure of construction of neural network models is illustrated in Fig. 3.

The performance of neural networks was estimated by the formulas $E_I(m) = \frac{\left\| \hat{f}_0^*(t) - f_0^*(t) \right\|}{\left\| f_0^* \right\|}$, where $f_0^*(t)$ is a desirable and $\hat{f}_0^*(t)$ is a real output value of the network. Applying the test data, we estimated the loss $\epsilon_I(m) = \frac{\left\| f_0(t) - f_0^*(t) \right\|}{\left\| f_0 \right\|}$, where $f_0(t)$ are the time series initial values. The results of estimates are shown in tables 1 and 2.

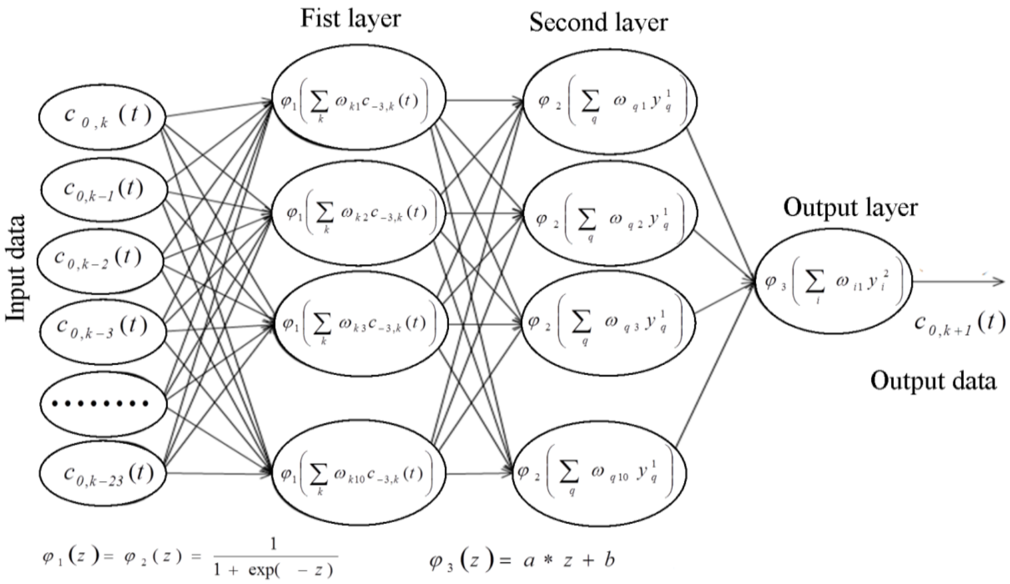

Fig. 3. Structure of construction of neural network schemes.

Analysis of the results in tables 1 and 2 shows insignificant increase of errors in winter time. Data losses are almost comparable for all the bases and also have seasonal dependence.

Table 1. Results of estimates of neural network performance (winter time)

m	Solar activity	ϕ	$E_I(m)$	$\epsilon_I(m)$	Tip effect dimension
3	low	Coif2	0,0042%	0,228%	40
3	low	Coif3	0,0011%	0,166%	64
3	low	Db2	0,0203%	0,213%	24
3	low	Db3	0,0057%	0,194%	40
3	low	Db4	0,0084%	0,201%	66
3	high	Coif2	0,0102%	0,281%	40
3	high	Coif3	0,0017%	0,164%	64
3	high	Db2	0,0334%	0,272%	24
3	high	Db3	0,0093%	0,236%	40
3	high	Db4	0,0154%	0,237%	66

Table 2. Results of estimates of neural network performance (summer time)

m	Solar activity	ϕ	$E_I(m)$	$\epsilon_I(m)$	Tip effect dimension
3	low	Coif2	0,0007%	0,117%	40
3	low	Coif3	0,0003%	0,111%	64
3	low	Db2	0,0137%	0,098%	24
3	low	Db3	0,0034%	0,124%	40
3	low	Db4	0,0027%	0,104%	66
3	high	Coif2	0,0006%	0,083%	40
3	high	Coif3	0,0002%	0,080%	64
3	high	Db2	0,0083%	0,089%	24
3	high	Db3	0,0033%	0,075%	40
3	high	Db4	0,0012%	0,087%	66

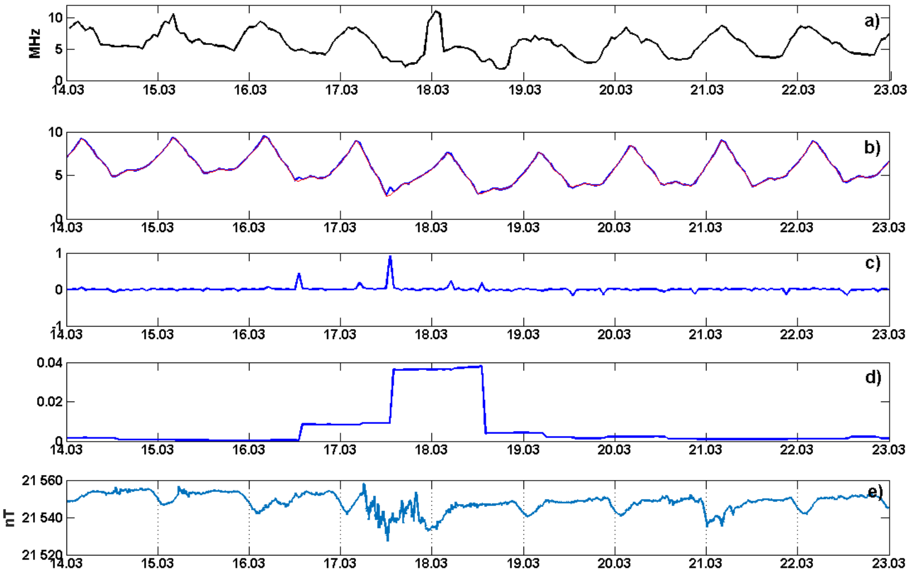

Fig. 4. Processing results of foF2 for 14.03 – 22.03, 2013 a) –foF2 data; b) –foF2 approximation, m = 3, Daubechies wavelt 3 (blue – initial data, red – model); c) – neural network errors; d) – error dispersion estimated in a moving time window that is equal to 24 counts; e) – H-component of the Earth magnetic field characterizes geomagnetic field state.

Fig. 4 shows the processing results of ionospheric F2 layer critical frequency parameters for the period of March 14 – March 22, 2013. A strong magnetic storm occurred on March 17 within the period under analysis. The network shows a small error of foF2 approximation (Fig. 4, graphs b-d) during undisturbed geomagnetic conditions (Fig 4, graph e). After the beginning of the magnetic storm (Fig. 4, graph e), errors significantly increase in the model (Fig. 4, graphs c, d). They show disturbance of the ionospheric parameter typical variation, that is determined by anomalous processes in the ionosphere.

3.2. Results of method application

Fig. 5 shows an example of processing of ionospheric data during a strong magnetic storm occurred on June 1, 2013. Processing results show anomalous behavior of the ionosphere during the magnetic storm and allow us to estimate the disturbance intensity in the ionosphere that confirms the efficiency of the suggested method. Analysis of neural network performance applying different wavelets (Fig. 5 d-h) shows that the dependence on the applied basis function is not significant and has a "cosmetic" character determined by the wavelet form. Application of a continuous wavelet transform and threshold functions (Fig. 5 b,c) allows us to obtain more detailed information on the ionospheric disturbance and estimate its parameters (intensity and duration).

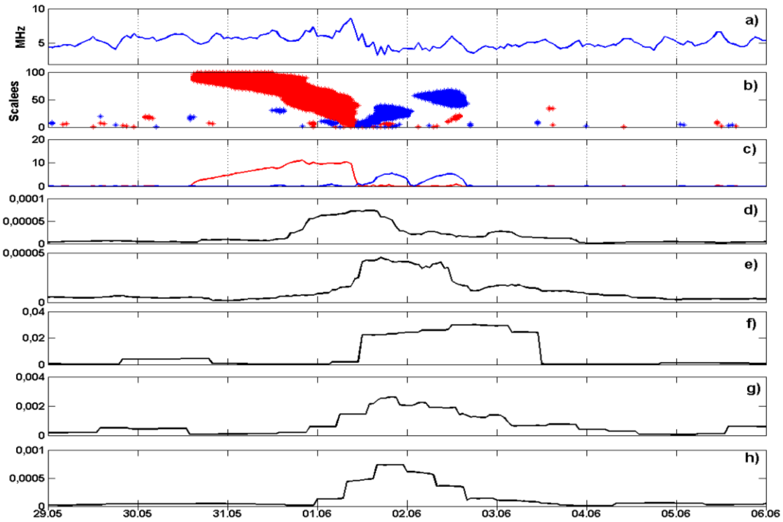

Fig. 5. Processing results of foF for 29.05 – 05.06, 2013 a) – foF2 data; b) – ionospheric anomalies (determined by relation (2), red– positive anomalies; blue – negative anomalies); c) – intensity of ionospheric anomalies (estimated by relation (3)); d) – h) –dispersion of neural network errors obtained by application of different wavelets: Coiflet 2 (d), Coiflet 3 (e), Daubechies 2 (f), Daubechies 3 (g), Daubechies 4 (h).

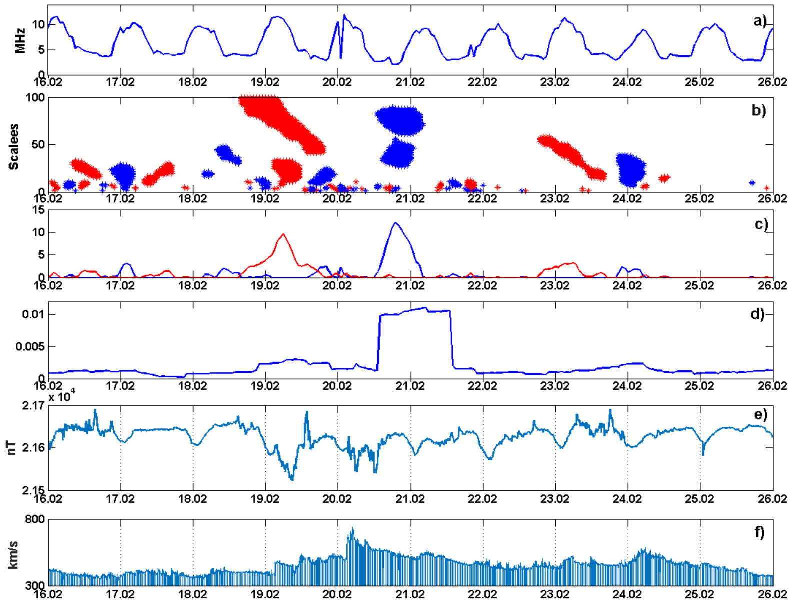

Fig. 6. Processing results of the data for 16.02 – 25.02, 2014 a) – foF2 data; b) – ionospheric anomalies (determined by relation (2), red – positive anomalies; blue – negative anomalies); c) – intensity of ionospheric anomalies (estimated by relation (3)); d) – dispersion of neural network errors obtained by Daubechies wavelet 3; e) – H-component of the Earth magnetic field; f) – solar wind speed.

Another magnetic storm under analysis which occurred on February 19-20, 2014 was recorded at Paratunka site (Kamchatka) within the period from 12:30 UT (Fig. 6). Based on the results of geomagnetic data processing, the strongest geomagnetic disturbances were observed on February 19 from 12:30 to 15:30 UT and on February 20 from 03:30 to 13:30 UT. The magnetic storm was initiated by accelerated fluxes from coronal mass ejection (CME on February 17) and recurrent coronal hole (http://ipg.geospace.ru). By the beginning of February 20, the solar wind velocity reached 750 km/sec. By the end of the day it decreased to 500 km/sec. Before the event, from 16:00 UT on February 18 to 19:00 UT on February 19, anomalous increases were observed in ionospheric parameters in the region of Kamchatka (indicated by red in Fig. 6). The anomaly maximum fell within the LT daytime. During the magnetic storm, electron concentration in the ionosphere significantly decreased (from 12:00 UT on February 20 to 04:00 UT on February 21, indicated by blue in Fig. 6). Results of modeling on the basis of neural network (Fig. 6, graph d) confirm the large-scale anomalous changes in the ionosphere during the event.

4. Conclusion

The proposed method showed its efficiency in the analysis of ionospheric data and allocation of the anomalies that occur during periods of ionospheric storms. Joint application of wavelet transform and neural networks allowed us to detect long periods of disturbances in the typical variation of ionospheric parameters. Application of continuous wavelet transform and threshold functions allowed to detect multiscale abnormal changes and to estimate their characteristics. The suggested computing solutions were implemented in software environment of free access (http://aurorasa.ikir.ru:8580, site mirror - http://aurorasa2.ikir.ru:8580).

Acknowledgements

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