



## Trend removal and filtering of TEC data by empirical mode decomposition

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### Abstract

This article describes a method of empirical mode decomposition that allows processing nonlinear and nonstationary signals. This method was used to remove the trend and filter the data of slant total electron content (hereinafter TEC). The results obtained are compared with the most commonly used approaches to processing total electron content data, which include digital filtering methods such as moving average filtering and removing the trend from the data of total electron content by subtracting approximating polynomials.

### 1 Introduction

TEC measurement using phase data of global navigation satellite systems (GNSS) signals reception is currently one of the traditional methods for solving problems of modern geophysical science [1]. TEC measurements were used to study sources of ionospheric plasma disturbances such as solar terminator, solar flares, geomagnetic storms, earthquakes, meteors fall, rocket launches, exposure to powerful ground-based radio emission, and others [2-8]. The study of various ionospheric irregularities and the search for their precursors is an urgent task today, since these irregularities can affect the propagation of radio waves and significantly reduce the reliability and noise immunity of ground-based and space-based radio systems. However, in order to get information about the magnitude and scale of the recorded irregularities, along with making measurements of the absolute values of TEC, it is necessary to distinguish the TEC variations caused by different ionospheric processes. To do this, first of all, remove the trend from the TEC data that depends on the change elevation angle of satellite and, accordingly, is associated with the distance from this satellite to the receiver's GNSS, and then perform the digital filtering procedure. Methods such as moving average and subtraction of approximating polynomials are most often used to remove a trend. Digital filtering methods such as moving average, Butterworth filters of various orders, and others are used to select TEC variations.

The method of empirical mode decomposition of signals used in this paper is relatively new, but no less reliable. This method is suitable for processing TEC data, since it works with nonlinear and nonstationary signals, which classical methods such as Fourier transform cannot afford, and does not contain the limitations of wavelet analysis,

since it does not require a priori information about the signal to select the base function.

In this paper, we consider and implement a method for removing a trend from the slant TEC data and filtering them based on the empirical mode decomposition method.

### 2 Empirical mode decomposition method

In nature, we most often deal with nonlinear and nonstationary signals, for the analysis of which an adaptive basis is required, which would be obtained in the course of a certain method from the signal itself. This method was proposed by Norden Huang in 1995 and called the empirical mode decomposition method. In 1998, the method was extended by the Hilbert transform and generalized to analyze any time data [9-11]. It is often used in studies of climate change, ocean waves, in the analysis of satellite, geophysical, meteorological and biomedical data, etc. [12-14]. This method is purely empirical and does not need a priori information, which makes it highly adaptive to various tasks [15, 16]. In a number of papers, it is shown that the method of empirical mode decomposition is superior to wavelet analysis in terms of frequency-time resolution [17].

The empirical mode decomposition method is the first stage of the Hilbert-Huang transformation. The second stage is the Hilbert transformation. It is used to calculate the instantaneous amplitudes and frequencies corresponding to each component of the decomposition, and on their basis, the instantaneous Hilbert spectrum of the input process is constructed. The latter will not be discussed in this work.

The method of empirical mode decomposition of a signal is an empirical method for decomposing any source signal, including nonlinear and nonstationary, into components called intrinsic mode functions (IMF) and residual trends that are not set in advance. The latter are the basis of the studied signal, obtained from it empirically, as a result of decomposition. Each IMF is an oscillatory process that, unlike a harmonic signal, has frequency and amplitude modulation. Moreover, each subsequent selected mode has a lower frequency.

It is necessary that every IMF corresponds to the following statements:

1) the difference between the total number of extreme points and the number of intersections of this function with the abscissa axis must not exceed one.

2) at any point in the function, the average value between their upper and lower envelopes obtained by approximating local maxima and minima, respectively, must not be different from zero.

IMF are defined as follows. Initially, local maxima and minima of the process are found, which are used to construct the upper and lower envelopes of the process using the cubic spline method. Next, a function of the average values of the found envelopes (local trend) is defined, which is then subtracted from the original process. As a result, the first approximation to the first IMF will be obtained. Further, the previous actions are repeated again over the received fashion estimate, and this happens until the residual criterion is reached. And as a result, the first IMF will be obtained. To find the next IMF, you need to subtract the already found IMFs from the original signal and repeat the described procedure again. This continues until all IMFs are found, that is, when the remainder does not contain extremes. As a result of decomposition, a finite number of IMFs and the resulting remainder are extracted from the original signal, which is either a constant value or a slowly changing trend.

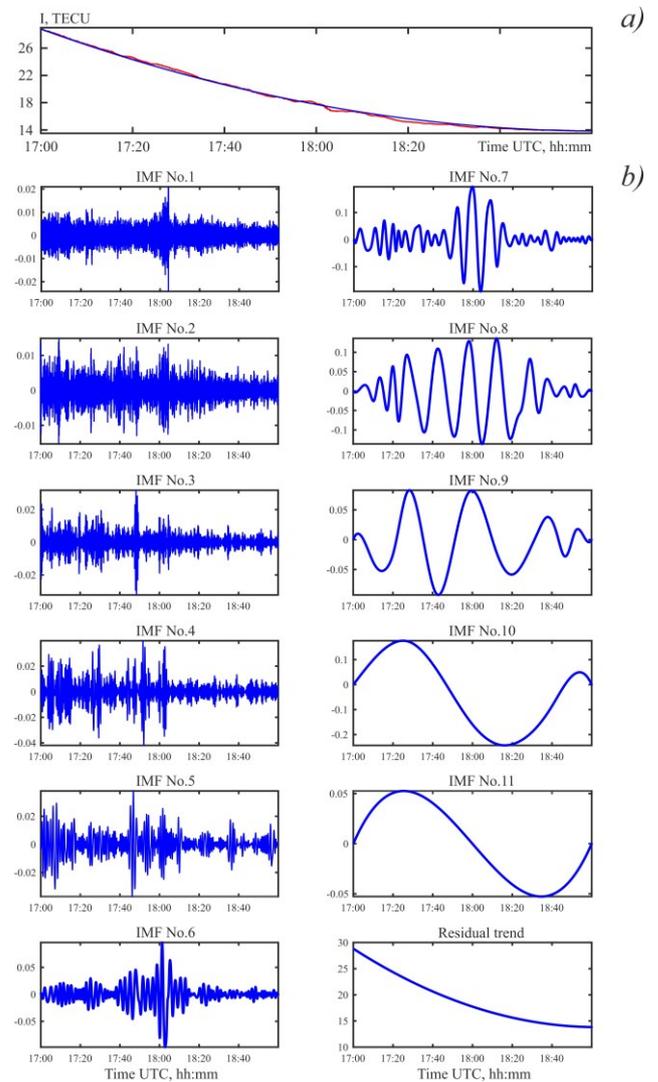
Each resulting component can be mapped to a separate physical process that caused it to occur.

### 3 Discussion of results

For data processing, a program was written that implements the method of empirical mode decomposition. By applying this program to the existing TEC data, the residual trend was effectively removed from the slant TEC data.

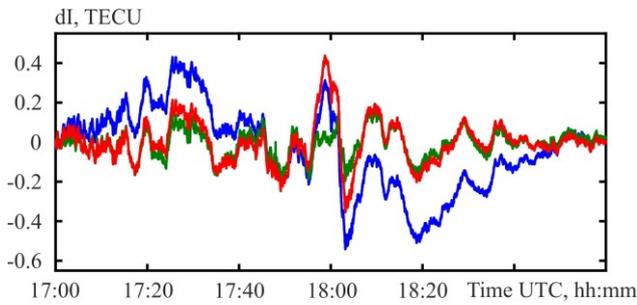
In addition to the trend, using the method described above, we were able to isolate fluctuations of various scales contained in the signal in the form of separate IMFs ordered by frequency from the TEC data. In this case, 11 IMFs are selected (see Fig. 1b) responsible for various physical processes. Due to the integral nature of TEC measurements, the study of individual IMFs, as well as the physical processes responsible for their formation and contribution to the overall TEC picture, requires a separate detailed study and has not been carried out in this work.

As mentioned earlier, obtaining a residual trend using the empirical mode decomposition method is the result of selecting IMFs from the TEC data, which in total represent TEC variations after the trend is removed.



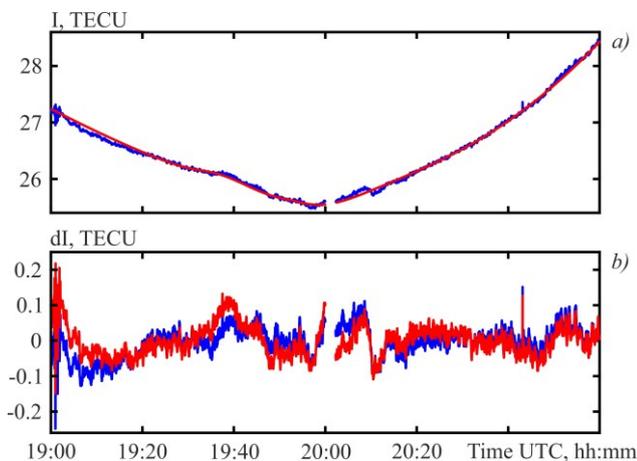
**Figure 1.** Panel a – slant TEC dependence on time is shown in red line, and the residual trend obtained by empirical mode decomposition is shown in blue line. Panel b – all IMFs selected using this method and the residual trend located in the lower right corner.

TEC variations can be obtained by various methods. Results of applying different methods to the same TEC data (the red line in Fig. 1a) are shown in Fig. 2. The results obtained after removing the residual trend using the empirical mode decomposition method are shown in the blue curve in Fig. 2. The TEC variations obtained by subtracting the approximating polynomial of the sixth degree, followed by filtering the series and only digital filtering by the moving average are represented by the green and red lines, respectively.



**Figure 2.** Variations of TEC, obtained by various methods of trend removal. In blue line, the TEC variations obtained after removing the residual trend by the empirical mode decomposition method are shown; in green line, the TEC variations obtained by subtracting the moving average; in red line, the TEC variations obtained by subtracting the approximating polynomial of sixth degree and followed filtering the obtained data by the moving average.

The last two methods do their job well if reliable information is known a priori about the processes that cause certain ionospheric perturbations, i.e. we know exactly the upper limit of the range of periods of studied variations associated with the response to a particular source of perturbation of the ionospheric plasma. But most often, when studying natural disturbances in the Earth's ionosphere, the source of their excitation is either unknown, or we are dealing with a summing response in the signal. In this case, the contribution of various physical processes to the TEC, including due to its integral nature, is difficult to determine. Therefore, it is more reliable, especially in the conditions of automatic processing of large arrays of GNSS data, to remove the trend using empirical mode decomposition of the signal, which does not require a priori information.



**Figure 3.** Example of removing a trend from TEC data that contains a break. On the top panel, the blue color shows the TEC's time dependence, and the red color shows the residual trend obtained by the empirical mode decomposition method. In the lower panel, the blue color shows the time dependence of the TEC variations obtained by removing the residual trend using the

empirical mode decomposition method, and the red color shows the TEC variations obtained by subtracting the moving average.

The empirical mode decomposition method also allows you to remove a trend from TEC data that contains breaks (upper panel Fig. 3a). This makes it more convenient to use in automatic processing of big data of GNSS measurements, since it is not required, as in the case of the moving average method and high-order polynomials, to search for break points and process individual TEC data. The TEC variations obtained by empirical mode decomposition for the TEC data containing the break are represented by the blue line in Fig. 3b, TEC variations filtered by the moving average are shown in red line in Fig. 3b. As can be seen from Fig. 3b, the TEC variations obtained by both methods are very similar in both shape and amplitude.

## 4 Conclusion

It is shown that the method of empirical mode decomposition of the signal can be used to remove the trend associated with changes in the elevation angle of the satellite, and consequently, the length of the satellite signal path section passing through the ionospheric plasma. During the work, it was also found that this method allows you to remove the trend from the TEC data even if the data contains breaks. Despite the fact that the method does not have strict scientific and theoretical grounds and is completely empirical, the example of TEC data processing shows the correctness of its work and compares it with the most commonly used methods of trend removal and digital filtering of TEC data. The method used allows processing nonlinear and nonstationary signals, since it does not require any a priori data about the signal since the basis is extracted from the signal itself. This fact makes it possible to use it effectively in systems for automatic analysis and processing big data of GNSS measurements.

## 5 Acknowledgements

This work was supported by Russian Science Foundation – grant No. 19-72-00072.

## 6 References

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