The article [16] proposes a new technique for signal-to-noise identification and targeted suppression of magnetotelluric signals. This method is based on the fractal-entropy clustering algorithm, which automatically identifies signal areas damaged by common noise (square, triangular, and impulse waves), providing targeted noise suppression and preventing the loss of useful information during filtering. To implement the procedure, four characteristic parameters are used - the cellular method for calculating the fractal dimension, the Higuchi fractal dimension, fuzzy entropy, and approximate entropy. Compared to the traditional noise cancellation strategy, which 'blindly' applies a filter to the entire data set, the proposed method can automatically identify and purposefully suppress intermittent noise in the signal. The resulting resistance-phase curve is more continuous and smoother, and the tendency of a slow change in the low-frequency range is maintained more accurately.

The article [17] describes the application of a two-stage computational methodology of five different methods for analyzing evolving chaos (DFA, analysis of fractal dimension using the Higuchi, Katz and Sevchik methods and power analysis). All analysis methods showed results that exceeded the threshold values for the data. Numerous stable segments were found with DFA values between $1.6 \leq \alpha \leq 2.0$, fractal dimension from $1.4 \leq D \leq 2.0$, and exponential exponent from $2.2 \leq \beta \leq 3.0$. Activity has also been reported in identical time windows between or after these earthquakes.

The works considered above confirm that both the fractal dimension calculated using the Higuchi algorithm and its dynamic change in time can serve as good parameters characterizing the dynamics of the studied time series.

The purpose of this work is to study the possibility of using the fractal dimension of time series, calculated using the Higuchi algorithm when processing the results of instrumental measurements and automating the procedure for detecting signals generated by irregular natural phenomena.

2 Equipment and research methods

The work presents the results of studies of time series, which are infrasonic signals, digitized using the equipment developed in the laboratory of robotics GASU [8]. To conduct infrasonic instrumental monitoring, several infrasonic sensors were used with a sensitivity of the order of 0.025 Pa at frequencies from 0.1 Hz to 1 Hz and 0.01 Pa at frequencies from 1 Hz to 5 Hz, developed on the basis of specially selected electrets microphones, the signal from which was amplified by an original module containing a high-impedance repeater on an operational amplifier, a signal amplifier and an active low-pass filter with a cutoff frequency of the order of 5 Hz. In addition, the sensors were installed at spatially separated measuring points of the polygon in conjunction with ultra-low-frequency resonators of various designs.

Measurements using the sensors listed above were carried out under the control of Atmega328 microcontrollers (Arduino Nano platform). All data were digitized using 16-bit analog-to-digital converters with a sampling rate of about 10-12 Hz and recorded via a galvanically isolated serial connection into asynchronous dataloggers with external quartz frequency stabilization, equipped with a real-time clock and having a special correction function implemented using a GPS receiver with an accurate 1pps timing signal. Data loggers were developed on the basis of the PIC24FJ64GA102 microcontroller in various designs and showed fairly good reliability characteristics over a long period of operation. It should be noted that meters and data loggers are practically autonomous measuring systems, limited in our case only by the presence of an external power supply and the volume of the used SD\MMC card.

Several functions have been written in Python language to carry out computational experiments. The listing of the function Lx (x, k) for calculating the length of the curve L(k) depending on the time interval k by the Higuchi method is presented below.

```
def Lx(x,k):
    xL=np.zeros(k)
    N=len(x)
    for i in range(k):
        m=i+1
        xx=x[i::k]
        dx=np.diff(xx)
        adx=np.abs(dx)
        nn=(N-m)//k
        sx=np.sum(adx[:nn])
        p=float(N-1)/(nn*k)
        L=float(sx*p)/k
        xL[i]=L
    Lm=np.mean(xL)
    return Lm
```

Also, a function was developed to calculate the actual fractal dimension HigFunc(xx1). In addition to the sought-for value of the fractal dimension, this function returns the vectors of k-values (time intervals) was taken the logarithm by base 2 and by base of the lengths of the curves L(k).

```
def HigFunc(xx1):
    NN=len(xx1)
    rr=NN//2
    xxx=np.zeros(rr)
    yyy=np.zeros(rr)
    k1=1
    logL=1
    jj=11
    ko=0
    z=0
    while k1 < rr and logL>0:
        if k1>=4:
            k1=2**((jj-1)//4)
            jj+=1
        if k1<rr and k1 != ko:
            ko=k1
            L=Lx(xx1,k1)
            logL=np.log2(L)
            logK=np.log2(k1)
            xxx[z]=logK
            yyy[z]=logL
            z+=1
        if k1<4:
            k1+=1
    x_x=xxx[:z-1]
    y_y=yyy[:z-1]
```

```
    fp, residuals, rank, sv, rcond = sp.polyfit(x_x, y_y, 1, full=True)
    f=sp.poly1d(fp)
    D=-fp[0]
    return x_x,y_y,D
```

In addition to the aforementioned functions, a time series smoothing scheme was implemented by processing the data with a simple normalized difference filter, preprocessed by performing a coenvolution (convolution) operation with a Gaussian kernel having a size of 25 samples and a standard deviation of 3.

3 Results

Before proceeding with the study of infrasonic signals, it was decided to use the recommendation of the author of the article [1] and reduce the number of investigated time intervals k. It was also decided to exclude from consideration those time intervals k for which the values of log2(L(k)) took values less than zero.

Before starting computational experiments with fractal dimension, a test set Y (i) (i = 1,2, ..., N) was generated by performing for each Y (i) summation of 1000 + i normally distributed numbers with zero expectation function and standard deviation equal to 1. $N = 2^{17}$ was chosen based on the data of the example from the article [1]. The generation procedure was implemented in Python language and looked:

```
N=131072
y=np.zeros(N)
for i in range(N):
    a = np.random.normal(loc = 0, scale = 1, size = 1000+i)
    y[i]=np.sum(a)
```

The results of the calculating are shown in Figure 1. The top graph shows the analyzed time series, and the bottom graph represents the points corresponding to the lengths of the flat curve, depending on the time interval k, presented in a double logarithmic scale. The required fractal dimension of the time series is calculated from the angle of inclination of the straight line drawn through these points, taking into account the least-squares method.

It is noteworthy that the algorithm we have implemented for the test suite, implemented by executing the program code presented above, in our opinion, implementing the recommendations proposed by Higuchi, consistently gave a dimension close to 2, while in [1] it is said that the set obtained by a similar algorithm should have a fractal dimension of 1.5. The fact that the expected dimension does not coincide with the calculated one may indicate either that the implementation of the algorithm for calculating the fractal dimension was performed with an error, or that the test array was generated not quite correctly.

Nevertheless, the software implementation of the algorithm for calculating the fractal dimension obtained by us in Python gave stable results for various test sets, which were invariant to a change in the scale of the sample under study, both in time and in amplitude.

Based on this, it was decided to carry out computational experiments using the software version we obtained for calculating the fractal dimension of the time series.

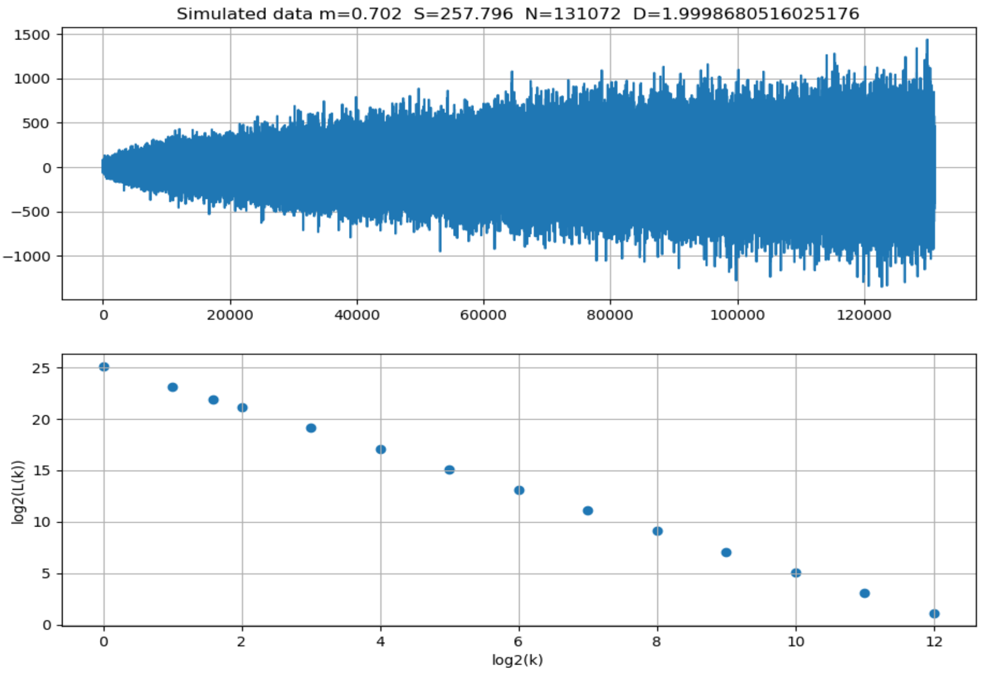

Fig. 1. The modeled time series and points of the straight line, by the slope of which the fractal dimension is calculated.

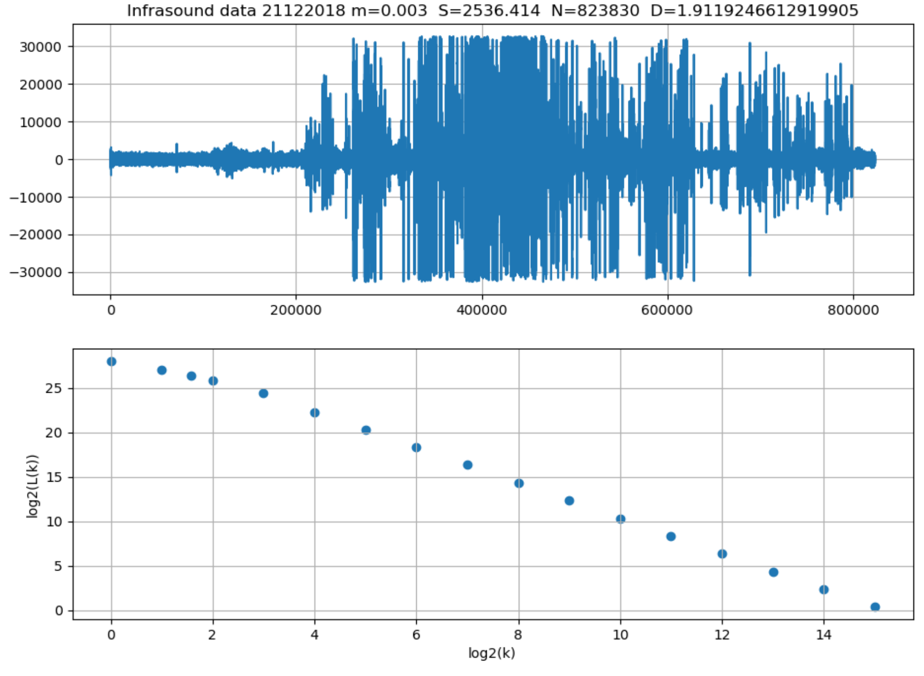

Fig. 2. Time series with an infrasonic 'event'.

The next step in the computational experiment was devoted to calculating the fractal dimension of the daily time series containing the signal received from the infrasonic 'event'. It should be noted that the calculation of the required fractal dimension gave us nothing.

Visual analysis of fragments of the studied time series showed a significant change in the type of the observed signal during the recording of data from the observed infrasonic 'event'. Based on this, a hypothesis was put forward that the fractal dimensions of the segments of the time series before the observed event and during the observed event should change. As a training sample, we had to select signals of phenomena of sufficient power, for which the time of their appearance would be known exactly. Thus, the daily time series of the days when the Proton rocket was launched from the Baikonur cosmodrome were selected. Infrasonic sensors recorded the moments of separation of the stages of the carrier rocket. Figure 3 shows one of these signals

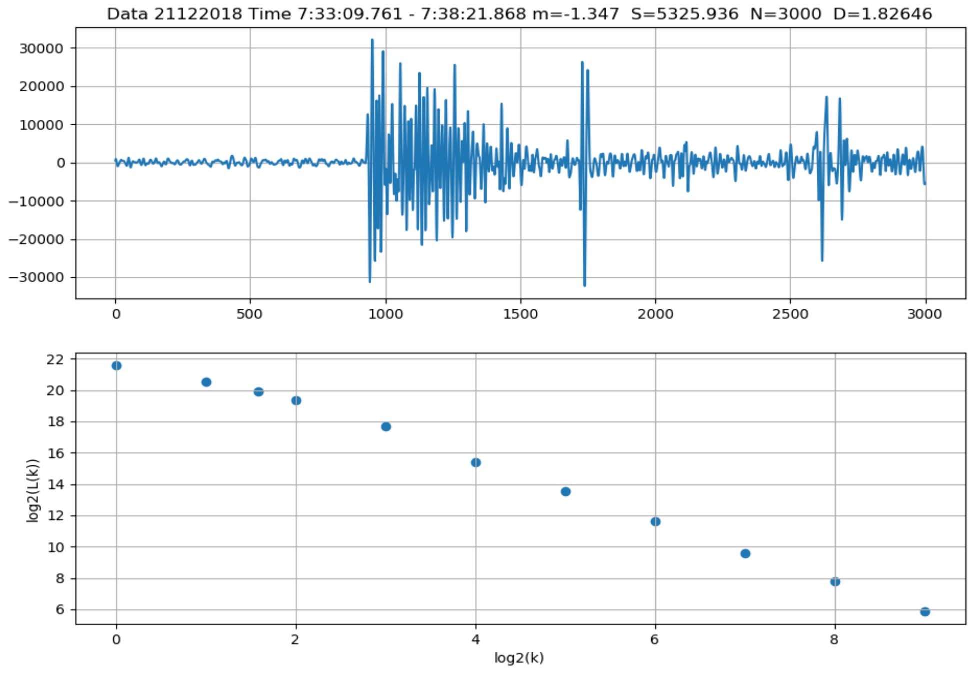

Fig. 3. Signal from the falling stages of the launching rocket Proton.

The computational experiment showed that the fractal dimension of the time series before the moment of fixation of the phenomenon and after the start of fixation of the phenomenon are really different, however, it was necessary to accurately determine the time (ordinal number of counts) that recorded this event. As a result of calculating the fractal dimensions of various fragments of the time series before the 'event', during the 'event' and after it, it was noticed that the values of the fractal dimension of the investigated fragment of the time series, where the beginning of the 'event' falls, noticeably changes. It was empirically determined that a sufficiently distinguishable jump in fractal dimension for signals of different amplitudes can be observed when segmentation of the time series at our disposal with a step of 250 samples.

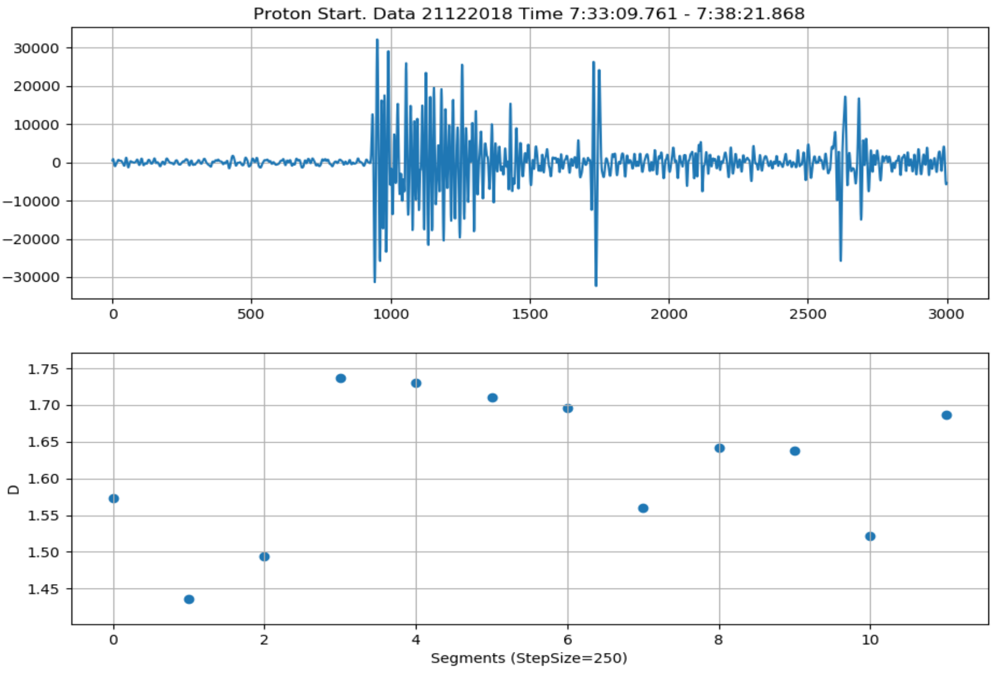

Fig. 4. 'Event' signal and fractal dimensions of time series segments.

In Figure 4, the upper graph shows the signal of the desired infrasonic 'event', and the lower graph shows the values of the fractal dimensions of the corresponding intervals of the time series, segmented with a step of 250.

It is important to note that the sampling rate of the signal was about 10 Hz, and the period of most of the investigated signals of "events" corresponded to 10 samples, i.e. about 1 Hz. Thus, a segment of a time series could include about 25 signal periods. It is possible that these ratios of the segment length and the period of the sought-for 'event' signal can be useful when working with signals that are excited by phenomena of a different energetic order and, accordingly, having other wavelengths of infrasonic signals.

In the course of analyzing the fractal dimensions of segments of different time series, it was noted that practically every investigated time series contained jumps in dimensions in time intervals, including the desired 'event' and in time intervals different from the presence of the phenomenon under study. Moreover, in such time intervals ('empty segments'), as a rule, various low-amplitude noise signals were presented. In other words, finding the moments of change in the fractal dimension of the segments of the time frame did not lead to an accurate and unique solution to the problem of identifying an 'event'.

As a result of the analysis, a hypothesis was put forward that for the temporary identification of an 'event' it is necessary to use at least two parameters that reinforce each other - fractal and amplitude. So it was decided to conduct an experiment with the calculation of the element-wise product of the components of the vectors of changes in fractal dimensions and changes in the average amplitudes of the investigated time series.

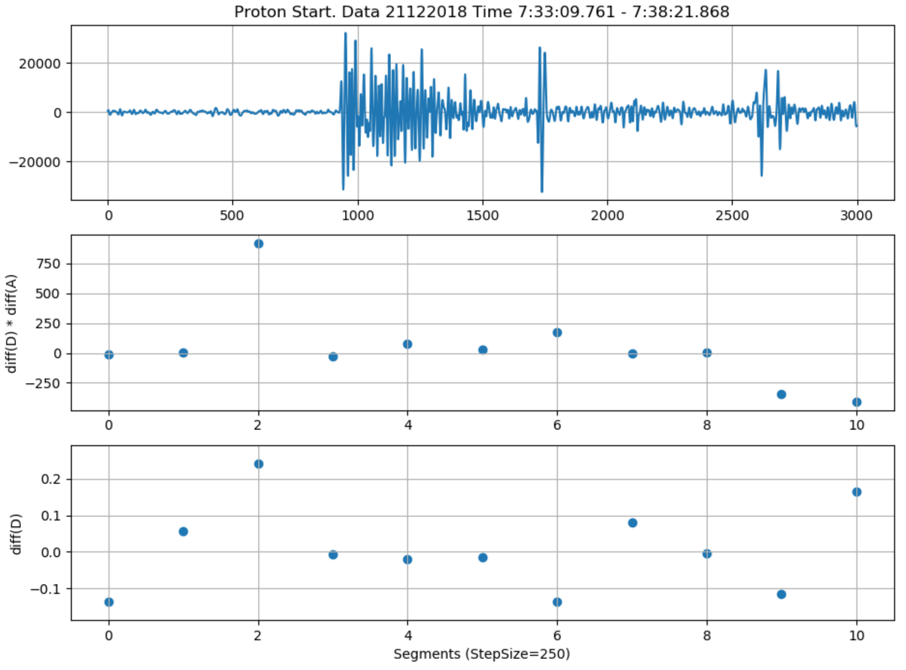

Fig. 5. The result of testing the hypothesis of element-wise multiplication of vectors containing jumps in fractal dimensions and amplitudes jumpings.

To test the hypothesis put forward, not only the fractal dimension, but also the expectation function of the signal amplitude was calculated on segmented time intervals, and then, using the numpy.diff() function, vectors of amplitude and fractal dimensions “jumps” were found. Next, performed element-wise multiplication of the vectors of "jumps" of amplitudes and fractal dimensions. The result was expected and positive. As you can see in Figure 5, the graph of the points of the resulting vector of element-by-element products contains the maximum value corresponding to the time interval of the sought-for 'event' signal.

Figure 6 and Figure 7 (scaled version) show the results of a computational experiment of the signal detecting of the desired infrasonic “event” in daily data.

As seen, visually detecting an 'event' with a graph of daily infrasound monitoring data in front of the eyes is a very problematic task. At the same time, the use of our proposed approach allows us to detect the desired event' with an accuracy of the segment number.

Figures 8 and 9 show the results of a computational experiment to search for an infrasonic 'event' in the time series data from 10/09/2019.

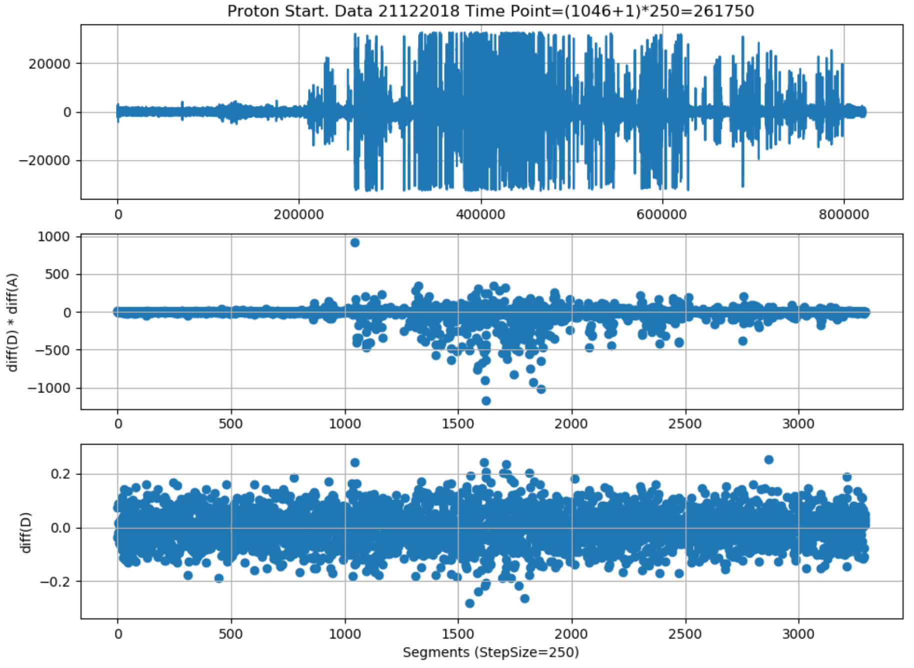

Fig. 6. The results of a computational experiment with a vector of products of fractal dimension differences and amplitude differences for an 'event' dated 12/21/2018.

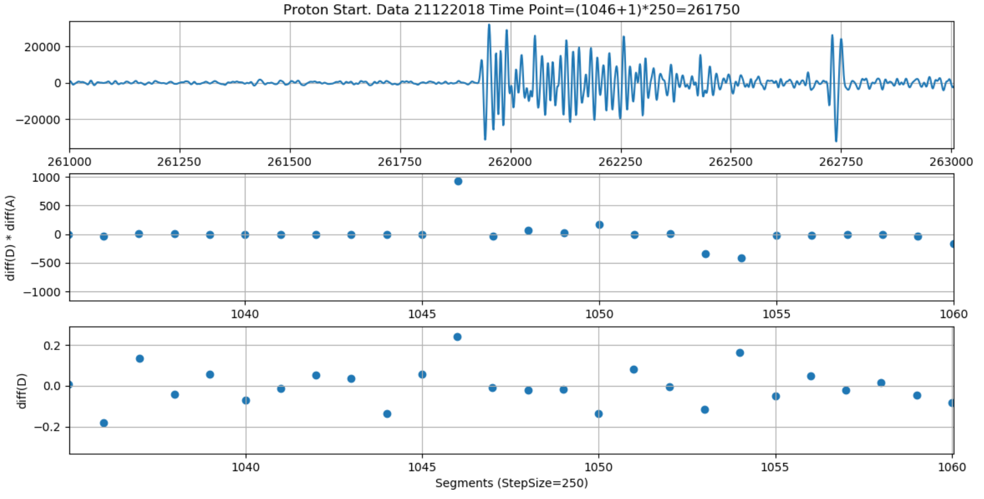

Fig. 7. Results of a computational experiment for a daily time series from 12/21/2018 (scaled).

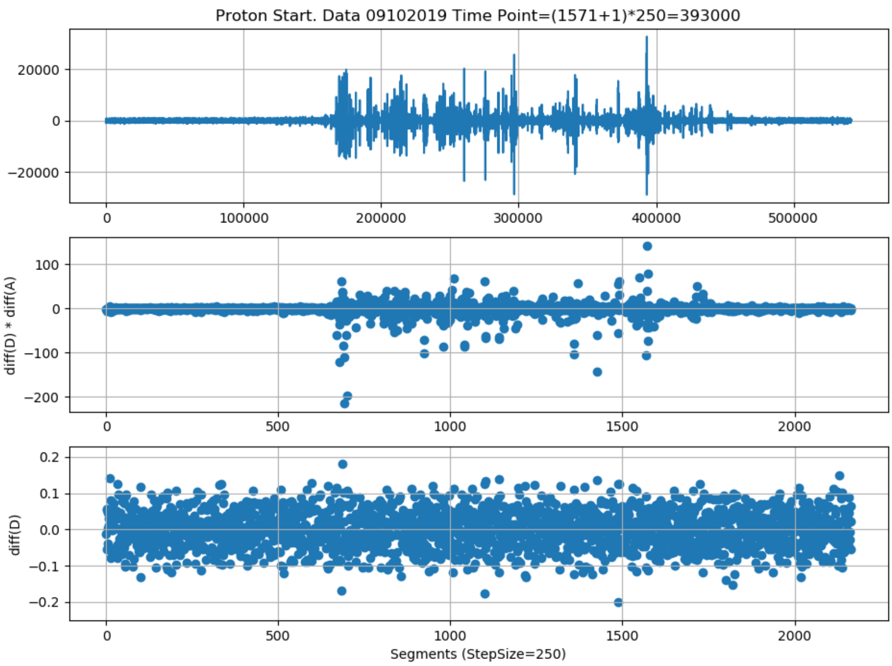

Fig. 8. The results of a computational experiment with a vector of products of fractal dimension differences and amplitude differences for an 'event' dated 10/09/2019.

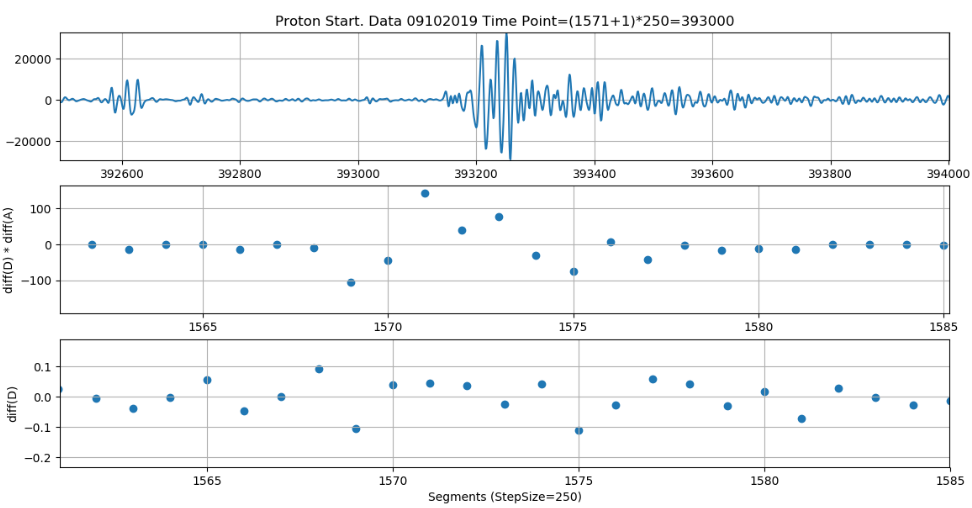

Fig. 9. Results of a computational experiment for a daily time series from 10/09/2019 (scaled).

4 Conclusion

In the process of studying the time series of infrasonic signals obtained as a result of measuring experiments, a number of regularities were discovered that make it possible to propose an original heuristic scheme (procedure) for processing and transforming the studying signal. The proposed approach makes it possible to determine the time intervals of the fragments of the investigated measurement results corresponding to natural phenomena causing infrasonic waves.

The essence of the used heuristic procedure is to perform the following steps:

• preparation of a time series by processing the data with a simple normalized difference filter, pre-smoothed by performing a coenvolution (convolution) operation with a Gaussian kernel;

• determining the step of segmenting the prepared data array;

• calculating the vector of fractal dimensions and the vector of averaged amplitudes of the time series segments obtained in the previous step;

• calculation of vectors of differences of neighboring values (jumps) for the vector of fractal dimensions and for the vector of averaged amplitudes;

• element-wise multiplication of jump vectors of fractal dimensions and averaged amplitudes;

• finding the maximum values for the resulting vector of element-wise multiplication of jump vectors of fractal dimensions and averaged amplitudes of time series segments.

The timestamps of the maximum values found will correspond to the time intervals of the studied series corresponding to the sought-for irregular natural phenomena that generate infrasonic waves.

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