ISSN 2278-3091
Volume 9, No.3, May - June 2020
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse101932020.pdf
https://doi.org/10.30534/ijatcse/2020/101932020

Neural Network Classification of Space Plasma Parameter Discontinuities

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ABSTRACT

The technology of artificial neural networks has been applied in the technique of separating jumps in the recorded parameters of the cosmic plasma and magnetic field into classes corresponding to the known types of magnetohydrodynamic discontinuities. Classification of parameter jumps recorded on the WIND spacecraft in 1996-1999 made using a network of the form “Kohonen layer”. An algorithm is proposed for establishing the orientation of discontinuity surfaces from one-dimensional observations of jumps in solar wind parameters on spacecraft.

Key words: Artificial neural networks, magnetohydrodynamic discontinuities, solar wind parameters, space plasma, classification.

1. INTRODUCTION

In interplanetary space during its experimental study using spacecraft, various jumps in parameters or the so-called discontinuities (shock waves, tangential, contact, rotational). It is of interest to establish the types of discontinuities observed in the solar wind and the orientation of their fronts, and to study their stability [1-3]. Separate problems in the study of jumps in the parameters of the interplanetary plasma are devoted to solving the problem of determining the slopes of the discontinuity fronts [4-6]. For these purposes, the “minimum variance” method is usually used, which is based on the study of the behavior of specific plasma parameters (density, velocity, magnetic field components) obtained on one (single-spacecraft method) or several spacecraft (multi-spacecraft method). These methods are based on the modified mass conservation law and empirical models of discontinuities obtained from statistical data. The disadvantage of this approach is the frequent inseparability of tangential and rotational discontinuities and, accordingly, inaccuracy in determining the orientation of the fronts.

In contrast to the above-mentioned methods, our study develops a neural network technology for separating jumps in the recorded parameters of the cosmic plasma and magnetic field into classes that correspond to known types of magnetohydrodynamic (MHD) discontinuities [7-10]. The results of the classification performed are mandatory for establishing the orientations of the fronts. To perform the classification, an artificial neural network (ANN) of the form “Kohonen layer” was created, which allows automatic classification of jumps in the solar wind (PSW) parameters of the medium and interplanetary magnetic field (IMF) recorded on the WIND spacecraft. The results of ANN classification are compared with “manual” classification according to the algorithms implemented by ANN. The paper also proposed an alternative way to search for the orientation of fronts. This method is applicable after performing the jump classification. As a result, for the breaks of the established classes, the orientations of the planes of their surfaces are determined on the basis of one-dimensional observations [11-13]. A study was also conducted of the evolutionality of the shock waves found.

2. MATERIALS AND METHODS

The basis of the proposed classification algorithms is to analyze the ratio of parameters on MHD discontinuities, when the pressure is assumed to be isotropic, and the heating of the discontinuity due to the influence of external radiation is insignificant.

The classification, which is directly based on the conditions at MHD discontinuities, cannot be applied to

experimental data obtained from a single spacecraft, since the orientation of the discontinuity always remains unknown. The vector relations included in the conditions at discontinuities are useless [14-16]. To solve the classification problem, you can use only the scalar part of the conditions. This adapted part of the conditions is as follows:1) tangential discontinuity [17-19], which is characterized by the preservation of the sums of pressures before and after the jump in parameters, i.e. the condition $\sum P = P + \frac{H^2}{8\pi} = const$ is satisfied.
2) contact discontinuity [18], when the velocity and magnetic field are constant: $V = const$, $H = const$.
3) rotational discontinuity [20-22] is also observed at $V = const$, $H = const$, but with the additional condition that the plasma concentration before and after the jump should not change ($N = const$).
4) shock waves [21], which are characterized by an increase in plasma concentration, a constant value of the normal component of the magnetic field with increasing magnetic field (fast shock wave) or with decreasing field (slow shock wave) behind the shock.

In this paper, the classification of discontinuities was carried out according to one of the parameters N, | B | or a combination of parameters $\sum P = P + \frac{H^2}{8\pi}$ (1). The classification and its interpretation required the development of methods for conducting numerical experiments. Two scenarios (algorithms) were developed for this. According to the first algorithm, classification should begin with the separation of the jumps by the sum of the pressures $\sum P = P + \frac{H^2}{8\pi}$ (2), and according to the second, with the separation by the magnetic field [23-26].

The ANN created for use in the work is built on the principle of self-learning. The general idea of self-learning algorithms is that in the process of training, by means of appropriate correction of weights, connections between excited neurons are strengthened. This means that there is a correction and consolidation of the image corresponding to a specific part of the entire group of events under consideration. Thus, the network is able to generalize similar images, relating them to the same class.

To solve the classification problem, a self-learning ANN of the Kohonen layer type was designed and used. The architecture of the Kohonen layer and the algorithm for its adjustment suggests that for each input vector only one neuron will be activated (the winning neuron). For a given input vector, only one Kohonen neuron produces a logical unit, all the others produce zero. The Kohonen layer classifies input vectors into groups of similar vectors (fig. 1). This is achieved by adjusting weights such that close input vectors activate the same neuron. As a result of training, the layer acquires the ability to separate dissimilar input vectors [28].

The study used an artificial neural network type with a self-organizing map (Self-organizing Map - SOM) - this is the so-called A "competitive" neural network with teacherless training that performs the task of visualization and clustering. The idea of the network was proposed by an outstanding Finnish scientist in the field of artificial neural networks and machine learning, Professor Toivo Kohonen . He also owns the development of the well-known "Kohonen layer" as an element of a self-organizing map. The algorithms of training and architecture of ANNs that he proposed served as the basis for a large number of studies in the field of neural networks, due to which Kohonen considered the most cited Finnish scholar. Currently, the number of scientific papers on Kohonen maps is about 8000. T. Kohonen himself is the author of more than 300 publications and 4 monographs.

Any self-organizing map is a method of projecting multidimensional space into a space with a lower dimension (most often, two-dimensional). Often in the literature you can find the term "Kohonen model", which refers to the architecture and learning algorithms of self-organizing maps and their modifications. In addition to solving classification problems, similar modified neural networks are also used to solve modeling and forecasting problems. A self-organizing map consists of components called nodes (neurons). This network is trained without a teacher on the basis of self-organization. As you learn, the vector of neuron weights tend to the centers of the clusters - groups of vectors of the training sample. The number of network nodes (the number of classes) is set by the analyst. Each of the nodes is described by two vectors. The first is a weight vector that has the same dimension as the input data. The second is the coordinates of the node on the map. Usually nodes are placed at the vertices of a regular lattice with square or hexagonal cells. Initially, the dimension of the input data is known; according to it, the initial version of the map is constructed in some way [29].

In the learning process, the weight vectors of the nodes approach the input data. For each observation, the node most similar in weight vector is selected, and the value of its weight vector approaches the observation. The vectors of weight of several nodes located side by side are also approaching the observation, so if the two observations were similar in the set of input data, they would correspond to nearby nodes on the map. The cyclic learning process, sorting through the input data, ends when the map reaches an acceptable (predetermined by the analyst) error, or after completing a given number of iterations. The Kohonen model generalizes the information presented. As a result of the ANN operation, an image is obtained, which is a map of the distribution of vectors from the training sample. Thus, the Kohonen model solves the problem of finding clusters in the space of input images, as was done, for example, in [2, 4]. At the stage of solving information problems, the network relates the new presented image to one of the formed clusters, thereby indicating the category to which it belongs.

Consider the basic architecture of the Kohonen ANN and the learning rules in more detail using the example of the Kohonen network (or Kohonen layer), which consists of one layer of neurons [30].

The number of inputs of each neuron should be equal to the dimension of the input image. The number of neurons is determined by the degree of detail with which to cluster the set of defined images. With a sufficient number of neurons and successful learning parameters, the Kohonen ANN can not only highlight the main groups of images, but also establish the "fine structure" of the resulting clusters. At the same time, close maps of neural activity will correspond to close input images. The disadvantages of such a network are that the network does not make it possible to construct exact approximations (exact mappings). In this, the network is significantly inferior to multilayer networks trained by the method of back propagation of error. However, a clear advantage of the network is the simplicity of its architecture. It makes it possible to extract statistical properties from the sets of input signals [9, 11]. Kohonen showed that for a fully trained network, the probability that a randomly selected input vector will be closest to any given weight vector is 1/k, where k is the number of Kohonen neurons.

The architecture of the Kohonen layer and the algorithm for its adjustment suggests that for each input vector only one neuron will be activated (the winning neuron). Improving the accuracy of input signal mappings and, as a result, increasing accuracy in the classification problem can be achieved by using a complex of several Kohonen layers, which will already be a self-learning map. Its main difference from the Kohonen layer is manifested in the fact that during operation not only the winning neuron is activated, but also a group of its closest neighbors. As in the case of the Kohonen layer, the number of putative classes is determined by the number of neurons. The map allows you to "place" your neurons in multidimensional space. The only difference is that the neurons have no displacements, and multidimensionality is realized purely mathematically and is used to determine the group of nearest neighbors with the winning neuron to adjust their weights in the learning process [15-22].

In its simplest form, the Kohonen layer functions according to the rule "the winner receives everything." For a given input vector, one and only one Kohonen neuron produces a logical unit, all the others produce zero. The Kohonen layer classifies input vectors into groups of similar vectors. This is achieved by adjusting weights such that close input vectors activate the same neuron in a given layer. The Kohonen layer learns without a teacher. As a result of training, the layer acquires the ability to separate dissimilar input vectors [9]. It is difficult to predict which neuron will be activated upon presentation of a specific input signal. Consider the process of learning and classification according to the Kohonen algorithm using an example. Let it be required to divide a certain set of images into a finite, previously known number of classes. Each image for classification can be represented in the form of a vector, and the matrix of the totality of the input data will be a set of such solitary events. The number of neurons in the Kohonen layer is set when creating the network and is equal to the number of classes into which the input data is supposed to be divided. Each neuron is described by its weight , which is multiplied with each element of the input column vector. As a result, a matrix of weights is formed . In this matrix, the number of rows (k) is the number of neurons in the Kohonen layer, that is, the number of putative classes, and the number of columns (n) is equal to the number of elements in each input vector (image). In addition to its weights, each neuron is described by the amount of displacement, which is added to the corresponding product of the weight and input element. The total network response will be determined by the operator, which returns a sparse response matrix with the designation of the belonging of each input vector to its class.

Now consider the learning process of the Kohonen map [16]. Initially, the map weight matrix is also set according to the midpoint rule, and for each training cycle, all images are also randomly sorted and fed to the input. The winner neuron is defined in the same way (recall that there are no displacements of the card neurons). Next, the weight of the winner neuron and its neighbors is adjusted according to the algorithm for adjusting the nearest environment of the neuron (its surroundings). It is quite obvious that with the same radius of the neighborhood for a given neuron-winner, but with different dimensions of the Kohonen map, the number of neighbor neurons that will be allowed to adjust their weights will be different and increases with increasing degree of dimension. The dimension of the map is set during its creation and does not depend on the dimension of the classified phenomena. Learning the Kohonen map continues in two stages - ordering the elements of the network weight matrix in the space of input vectors and fine tuning the parameter of the learning speed and the size of the neighborhood of the winning neuron [10]. At the stage of ordering, the initial size of the neighborhood is set equal to the maximum distance between the neurons for the selected topology (often the location at the nodes of the rectangular grid is chosen). Further, it decreases according to a well-known rule. At the fine-tuning stage, the size of the neighborhood does not change, and the parameter of the learning rate is adjusted and decreases very slowly. The small value of the neighborhood and the slow decrease in the parameter of the learning speed fine tune the network while maintaining the location found in the previous step. As in the case of the Kohonen layer, the weights of the card neurons will be ordered so that with a uniform distribution density of the points of the input vectors, they would also be distributed evenly. If the points of the input vectors are not distributed evenly, then the points of weights of the neurons of the Kohonen map will tend to be distributed in accordance with the density of the input vectors [12, 16].

One of the most important properties of Kohonen's trained network is the ability to generalize. The vector of each of the network neurons replaces the group of classified vectors corresponding to it. This allows you to use this type of network in the field of data compression [5].

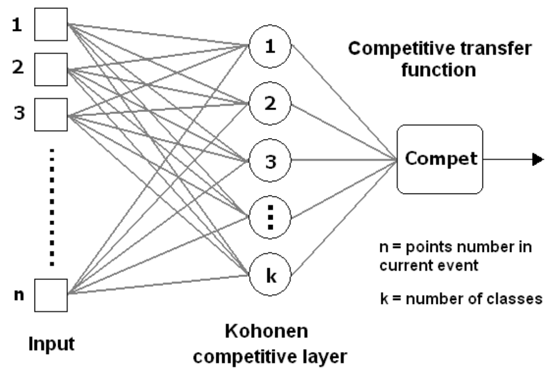

Figure 1: Kohonen neural network

Figure 1 shows us Kohonen neural network with points number in current event and number of classes.

Using the proposed methodology for the classification of solitary disturbances using ANNs, 82 discontinuities in the solar wind were analyzed, of which WIND was recorded in 1996-1999 for their separation by type. The efficiency of the neural network and the correspondence of the performed classification of the real situation is checked by comparing the results of two classifications (according to the first and second algorithms). In a successful case, the classification results for the first and second scheme should be close. As a result of calculating the percentage of coincidence of the classification results by two independent algorithms, it was found that in 87% of cases the network gives reliable results.

An additional study to verify the reliability of the performed neural network classification was to classify data on parameter jumps "manually" according to the algorithms used above. The purpose of the experiments was to compare the results of the classification performed by an artificial neural network and a laboratory assistant (natural neural network) [18]. A feature of manual classification is a more strict separation of parameters for specific classes. Unlike a neural network, which simultaneously works with one specific event (all other events at this time are conditionally present in the form of ANN tuning factors, and their "clarity" depends on the quality of network training), the laboratory technician has the opportunity to work with all cases at once. This advantage allows the natural neural network to operate with a full set of events simultaneously. Comparison of the results obtained by different methods (ANN, manual processing) made it possible to calculate the percentage of matches for different classification options. It amounted to 75%, which indicates the reliability of the created classification methodology.

A search is made for the orientation of the planes of the discontinuity surfaces in the space of the solar-ecliptic (SE) coordinate system. The main source of information in determining the orientation of the planes of specific discontinuities, in addition to information about the behavior of the components of the IMF vectors and the flow velocity, is the type of discontinuity that we established as a result of the classification. For rotational discontinuities and shock waves, the condition for the invariance of the magnetic field component normal to the surface of these types of discontinuities during the jump, Hn=const, was used. For tangential and contact discontinuities, the condition of the absence of magnetic field components and velocity normal to the surface of these types of discontinuities during the jump was used - Hn=Vn=0 (for tangential discontinuity) and Vn=0 (for contact discontinuity).

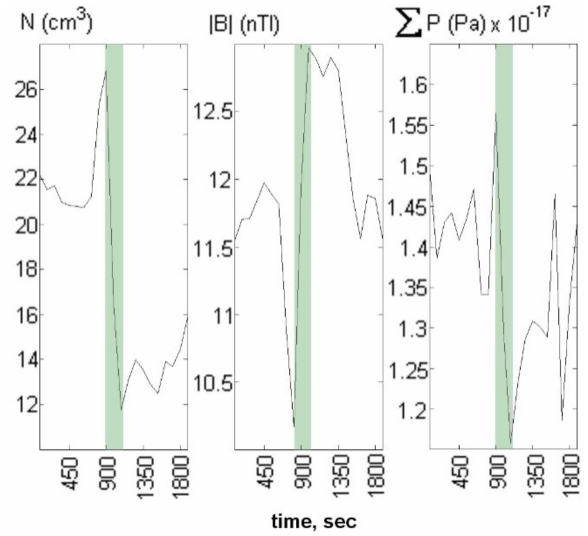

Figure 2: Parameters of the event 16/03/96 type contact rupture, obtained on the basis of measurements on the spacecraft.

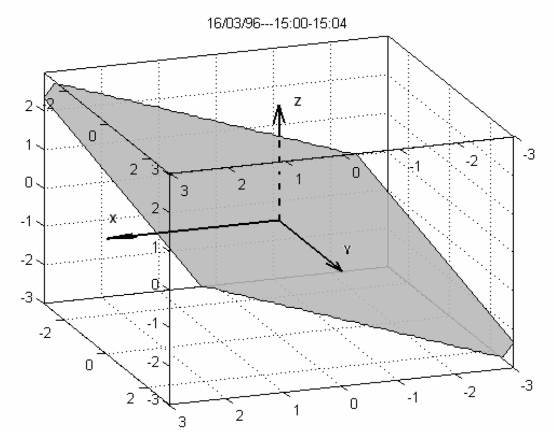

Figure 3: The calculated plane of the event 16/03/96 type contact discontinuity in the solar-ecliptic coordinate system in arbitrary units.

Figure 2 shows us the parameters of the event 16/03/96 type contact rupture, obtained on the basis of measurements on the spacecraft by neural network.

Figure 3 shows us the calculated plane of the event 16/03/96 type contact discontinuity in the solar-ecliptic coordinate system in arbitrary units.

Thus, using one-dimensional measurements, it was possible to obtain three-dimensional pictures describing the positions of the parameter discontinuities in the solar wind.

An analysis is made of the evolutionality of the established cases of shock waves in the coordinate system with the x axis normal to the plane front of the shock wave. In Fig. 4, according to the classical concepts, the regions are determined that correspond to the necessary and sufficient evolutionary (stability) conditions for shock MHD waves. V1 and V2 are the plasma velocity components with respect to the shock wave along the x axis before and after the discontinuity. Evolutionary shock waves correspond to areas with double hatching.

Two evolutionary waves correspond to evolutionary shock waves: fast V1> Vfms and slow Vsms<V1<VA (VA and Vfms/sms are the propagation velocities of Alfven, fast and slow magnetosonic waves).

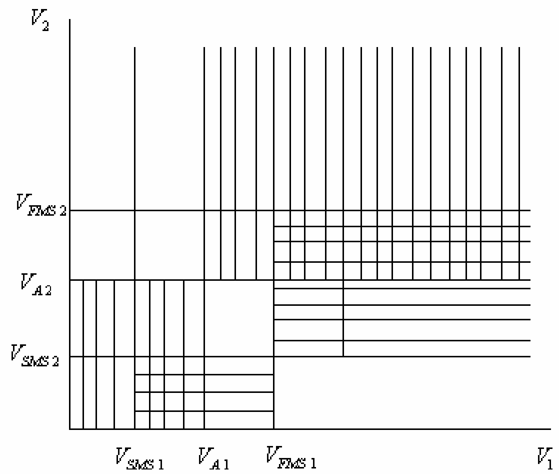

Figure 4: Areas for determining the evolutionality of shock waves.

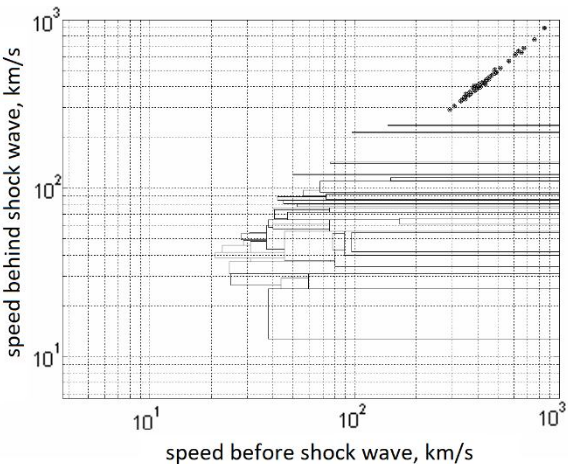

Figure 5: Regions of evolutionality and values of jumps in the velocity of the medium for the studied shock waves. Axes are represented on a logarithmic scale.

The ability to calculate the values of the speed of fast and slow magnetosonic waves for the shock waves established as a result of the classification allows us to show their evolutionary regions (see Fig. 4). For these cases in Fig. 5 points represent the speed of shock waves. As you can see, the points do not fall into the field of evolution, because speed is always greater than. However, this does not suggest that there are no evolutionary shock waves in the available sample. Because the the area in which our shock waves fell correspond to the necessary evolutionary conditions

3. CONCLUSION

In this paper, on the basis of the one-fluid MHD approach using the technology of artificial neural networks, we developed a technique for the automatic separation of jumps in the recorded parameters of the cosmic plasma and magnetic field into classes corresponding to known types of discontinuities. For this, a classification ANN of the form “Kohonen layer” was developed and a classification of jumps in the parameters recorded on the WIND spacecraft in 1996-1999 was performed. according to two different algorithms. The reliability of the network was checked and confirmed by comparing the results of both ANN classifications with the classification performed "manually" according to the same algorithms. To break the established classes, a method has been developed and applied to determine the orientations of the planes of their surfaces in the solar wind from one-dimensional observations on the spacecraft. An analysis of the evolutionality of the shock waves found is performed, which demonstrated their potential instability

ACKNOWLEDGEMENTS

This work was supported by RFBR grants No. 20-05-00327, No. 18-35-00430 and the State order of the Ministry of Education and Science of the Russian Federation No. 5.5898.2017 / 8.9.

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