PROBLEMS OF IMAGE PROCESSING AS APPLIED TO AUTOMATIC PROCESSING OF IONOGRAMS

V.P. Grozov, V.E. Nosov, and G.A. Ososkov

Institute of Solar-Terrestrial Physics,
Siberian Branch of the Russian Academy of Sciences, Irkutsk
Joint Institute of Nuclear Investigations, Dubna
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Diagnostics of an ionospheric channel is based on an analysis of ionograms of vertical, slant, and return-slant sensing. This analysis calls for a solution of two general problems: 1) ionogram processing, that is, the correction and improvement of images and selection of points (moments of arrival) of a signal; 2) tracing tracks through the points for their subsequent referencing to specific propagation modes. To solve the first problem, statistical methods of image processing are used. To solve the second problem, the Houpfield method of artificial neuron nets (ANNs) is used. Because of the complex character of tracks against the intense background noise the modified rotor model has been used. Proper choice of the initial configuration has provided the fast convergence of the net. Ionograms recorded with chirp-zonde at the ISTP, Irkutsk, in 1987–1996 has been used to check the model. Analysis of the results has shown that this approach gives good results. It is promising for ionogram processing.

INTRODUCTION

The basic tendency of ionospheric informatics is the decrease of the access time to current diagnostic information about the state of the ionosphere. Reception of new data in real time is of principal importance. First, this makes much easier organization of geophysical and radio physical experiments on the study of the ionosphere. Second, this is necessary for solving number of practical problems, especially in the framework of the modern concept of allocation of working frequencies for short-wave (SW) communication and radar sensing.

Large information flows can be processed in real time only in case of automatic ionogram processing for different regions of ionospheric sensing.

In general, the ionogram can be considered as a raster image of the range-frequency characteristic registered by an ionozonde.[1] Each pixel of the image (ionogram) is specified by two parameters: coordinates (frequency and delay) and brightness (amplitude) (Figs. 1–3*a*). Thus, the examined image can be represented in the form of $N \times M$ matrix of coordinates $A[F_i, D_j]$. As a result of processing, it is necessary to trace connected lines through characteristic points (determined by a certain criterion), that is, to trace tracks subsequently referred to a specific propagation mode.

In this problem formulation it is necessary:

a) to process the ionogram including image correction, that is, to perform pulse noise filtration, correction of the amplitude characteristics, noise suppression, and so on; to improve the image quality, that is, to increase image contrast, to identify fragments characterized by the connection property, and so on; to identify the signal characteristic points corresponding to physically significant characteristics of the image;

b) to trace tracks and to refer them to a specific propagation mode.

1. IONOGRAM PROCESSING

Problems of ionogram processing are closely interconnected by methods of their solution. These methods beam an the presence of characteristic noise whose properties is connected with the influence of a medium, the parameters of transceiving systems, and so on. Because the noise is present practically always, the image can be interpreted as random processes of two variables, that is, as random fields. Therefore, statistical methods of data processing,[2–6] can be used for image processing. Efficiency of the methods is determine by statistical properties of noise. A model of noise includes statistical description of pixels forming the image and the type of interaction between noise and signal.

As an image model, the standard Rayleigh model of distribution was used, and as an analytical description of the type of interaction between noise and signal, the multiplicative model was used. This model permits local methods of smoothing, highly efficient and

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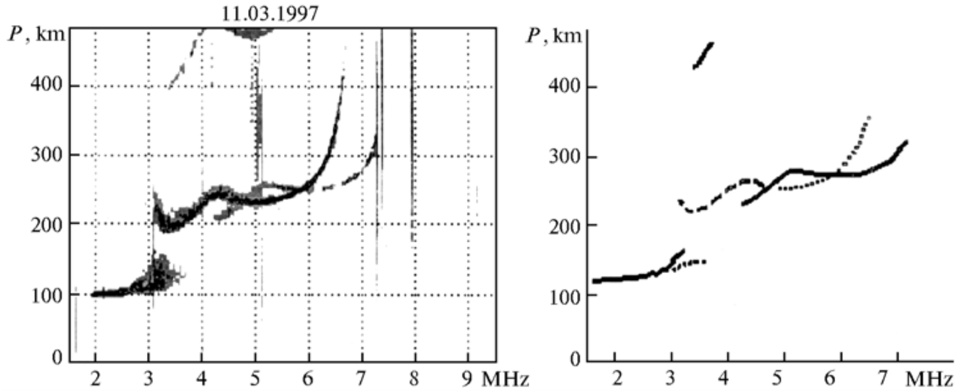
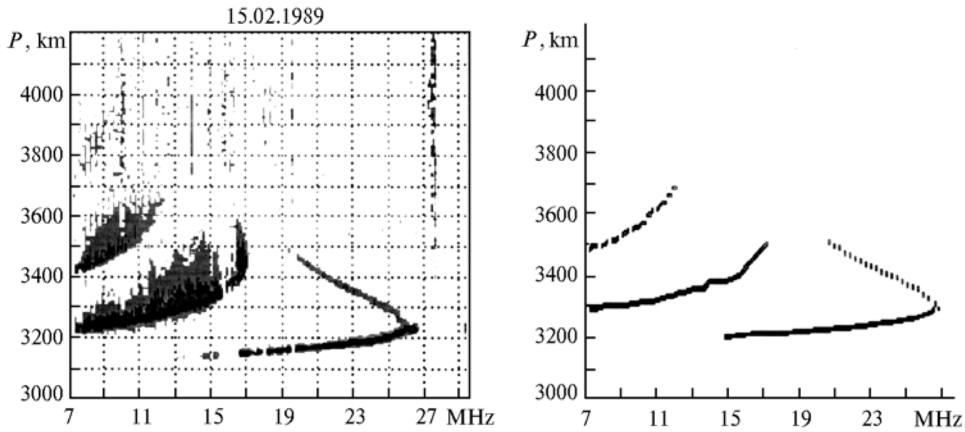
adaptable to the same character, to be used for image correction. These methods allow to estimate the field of unnoisy images by way of analysis and processing of a limited number of fragments having sufficiently small sizes. As a fragment of ionograms, a 5×5 square of points of matrix $\{A\}$ was used. Selection of these sizes was determined by the following conditions:



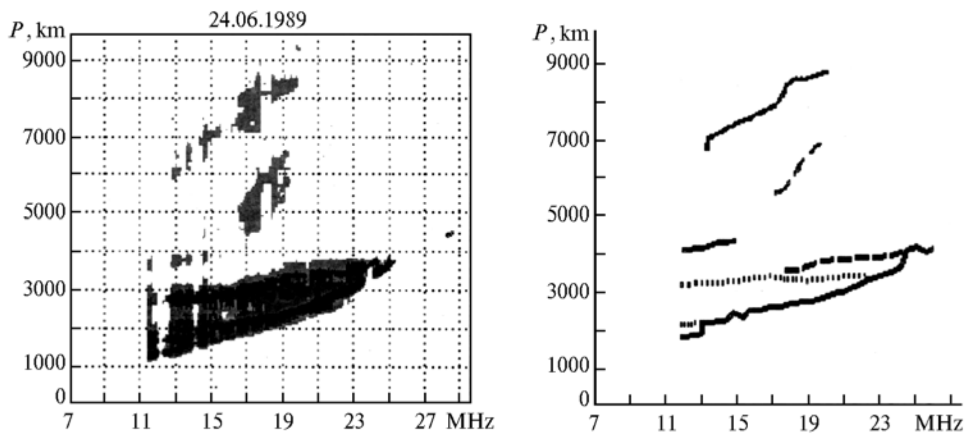
a *b*

FIG. 1. The vertical sensing ionogram.



a *b*

FIG. 2. The slant sensing ionogram.



a *b*

FIG. 3. The return-slant sensing ionogram.

a) band, where the signal remains practically unchanged;

b) sonde resolution;

c) requirements for sufficient statistics of the selected data volume and minimum computing time.

The image was processed in the regime of sliding fragment with overlap.

In the first stage, the data were corrected to eliminate vertical and point interference and to fill randomly emitted data. The correction was performed by the linear prediction method, when the corrected parameter was taken to be a sum of the parameters of adjacent pixels with some weights. In the present work, the following formula was selected[5]:

$$B_{i,j} = 0.3(A_{i,j-1} + A_{i-1,j}) + 0.2(A_{i-1,j-1} + A_{i+1,j-1}).$$

Pulsed interferences were removed using a medium filter.

When smoothing the noise, operations decreasing the noise level without blurring of the brightness gradients are of particular interest. Most efficient are the methods based on local ordinal statistics. Thus, to remove noise, a technique based on elimination of contributions to the averaged parameter of counts that did not satisfy the given model of uniformity was implemented. The idea of the technique lies in the fact that within a larger fragment window (for example, 5×5) fragments with smaller sizes (3×3) are selected. For each fragment the average and the standard deviation are calculated. The average brightness in the vicinity of pixel with minimum standard deviation is assigned to the central pixel of the fragment.[7] To increase the speed of operation, the expression

$$S(k) = \sum_{n=1}^{9} |(A_{i,j} - A_n(k))|, \quad k = \overline{1, 9}\ .$$

was used instead of the standard deviation as a criterion for uniformity. Here, A_{ij} is the brightness of the central point of the large fragment; $A_n(k)$ is the brightness of the nth point of the kth small fragment. In this case, A_{ij} was substituted by the mean brightness within the fragment with the minimum $S(k)$. It should be noted that this approach does not require any *a priori* knowledge and is fally determined by the scene character.

In the next stage, details of image were constructed using the nonlinear adaptive amplitude transform, which was constructed on the basis of measurement and analysis of a histogram of signal distribution. The function of signal transform was adjusted so that the transformed signal has the required distribution histogram. For the examined problems good results were obtained when the uniform distribution was used as an output distribution. The transform function in this case had the form

$$D = (\overline{D}_{\max} - D_{\min})P_A(A) + D_{\min}\ ,$$

where $P_A(A)$ is the distribution function of the initial image probability and $D_{\max}$ and $D_{\min}$ are the maximum and minimum levels of the transformed signal. The result of this transformation is the increase of contrast of the image fragments with most often occurring signal values.

Results of image constructing permits us to proceed to image segmentation by the methods of threshold processing. Because we can consider that threshold for the examined problems are constant in a certain vicinity of the image pixel and depend on the local image characteristics as well as on pixel coordinates we can use the processing methods with a variable threshold. The idea of processing lies in the fact that the brightness of the image is always nonuniformly distributed. Therefore, the selection of the appropriate threshold allows us to the recognize the fragments containing valuable information and noise.

Because to describe the brightness nonuniformity with any known function is a complicated problem, threshold estimations were implemented within a local fragment. If the fragment contains object and noise, its brightness histogram must be (at least) bimodal. The minimum brightness of the histogram for the pixel between the modes gives the local threshold for identification of the object against the background noise in the given image fragment. When the fragment contains only object or noise, it histogram is unimodal and the local threshold cannot be determined for it. In this case, it was assigned by the way of interpolation of the local thresholds determined for the nearest bimodal fragments. As a result, quasiuniform fragments were identified in the ionogram corresponding to signal modes.

Thus, as a result of implementation of the algorithms described above, we succeeded to a large measure in noise removal, noise smoothing, and data compression leaving only the points with maximum amplitudes. In the last stage, for the selected fragments we determined the moments of signal arrival taken to be the local maxima for each separated fragment. As a result, we obtained the image in the form of clouds (matrix) of points with significant amplitudes in the coordinates: group path length – working frequency (Figs. 1–3*b*). The matrix of points so obtained was used to trace the tracks and to interpret them.

2. TRACK TRACING

To trace the tracks, the method of artificial neuron nets (ANNs) was used that was successfully employed in high-energy physics.[8–12] Efficiency of the method is provided by the ability of neuron net to evolve to such equilibrium conditions, which correspond to the minimum of the energetic function. For proper choice of the weight function, the energetic function minimum must correspond to the optimum point distribution along the tracks. By virtue of the similary of the problem, the method of neuron nets was used for identification of tracks in the vertical sensing ionograms[9] and then for other types of ionograms.[10]

To solve the track identification problems in the ionograms, the Houpfield ANN (HNN) was selected.[11] The HNN advantage is in the ability of finding the optimum solution to a certain problem without preliminary learning by minimization of corresponding *a priori* assigned functional that contains the information about the solution. The HNN is the fully connected net, that is, the net that has the path of signal transmission from the neuron outputs to their inputs. A response of these nets to the external information is dynamic, because the calculated output passing through feedbacks modifies the input, after that the output is calculated once more, and all process is repeated. For the stable net successful operations lead to the achievement of the stable state.

Our analysis of ionograms (see Figs. 1–3*a*) has shown that the lines approximating tracks of one type strongly differ by their shapes and lengths. Thus, tracks of the ionograms cannot be fully described by straight lines or sections of circles. This makes their analytical description difficult. Therefore, only local approximation can be considered. For this aim, a circular arc is best suited: in this case, a track will be formed by arcs of different lengths and curvatures. Such a local character also must have neuron interaction. Because the ionograms are characterized by complex tracks against intense background noise, under these conditions the modified Houpfield rotor model was selected.

In the context of the HNN it was assumed that neurons are the rotors (Fig. 4). The dynamic variable is the angle. These rotors interact with each other and with the vector $\mathbf{L}_{ij}$ connecting them, that is, the neurons are characterized by their values, coordinates, and slopes. It was assumed that signals fall fairly well on a circle. And the neuron net should locate the vectors along the tangents to this circle and strongly decrease the vectors that do not lie on any actual track.

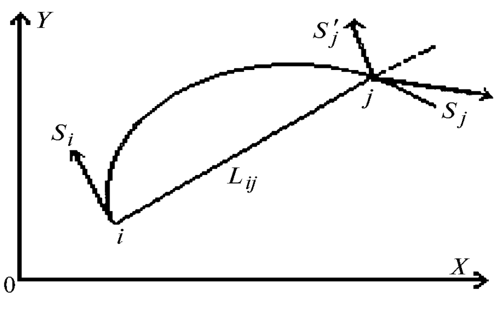


FIG. 4. Modified rotor model.

Thus, each neuron corresponds to the vector $\mathbf{s}_i$ whose modulus characterizes the intensity of influence of this neuron on the others and whose sense should ideally coincide with the tangent to the track. Because the track has variable curvature and salient points, only neurons of a certain local fragment can interact. This is achieved by introduction of a robust multiplier in the weight function T_{ij} that plays the role of the filter. Going to the field terms, we introduced the vector $\mathbf{h}_{ij}$ as a field generated in the point i by the neuron j

$$\mathbf{h}_{ij} = T_{ij}\,\mathbf{s}_i\,.$$

Then the total field H_i in arbitrary point can be determined as a vector sum of fields from all neurons

$$\mathbf{H}_i = \sum_j \mathbf{h}_{ij} = \sum_j (T_{ij}\,\mathbf{s}_i).$$

Considering the remarks about the local character, we assume that track is formed by neurons whose eigenvectors are closest in their senses to the field vector in this point. As a measure of proximity, it is convenient to take the scalar product of the vectors $\mathbf{s}_i$ and $\mathbf{H}_i$. Then the energetic function of the system can be written in the form

$$E = -\frac{1}{2}\sum_i \mathbf{H}_i\,\mathbf{s}_i = -\frac{1}{2}\sum_{i,j} \mathbf{s}_i\,T_{ij}\,\mathbf{s}_j\,.$$

Its minimum corresponds to the optimum point distribution along the tracks for the proper selection of the weight function.

The problem of track identification reduces to the organization of evolution of the neuron net states that provides its convergence to the configuration minimizing the system energetic function. An interactive procedure for search of this HNN configuration was constructed as a successive calculation of the field in the points of location of the neurons, determination by each neuron of its state, and assignment of a new value of the vector for the next interaction step. The new value of the vector modulus for the ith neuron was determined by the formula[12]

$$|\,\mathbf{s}_i\,| = \tanh(|\,\mathbf{H}_i\,|/T),\ \text{where}\ T = 1.5.$$

A new sense of the vector was assumed coincident with the field direction in the point. The vector thus calculated was used for determination of vectors of other neurons already in the given step of the HNN evolution. In the next step, all procedure was repeated. After some iterations (their sufficient number was determined by the smallness of the energetic function increment for the examined iteration), the vectors of neurons were aligned with a certain error in the direction of tangents to the track in the points of neuron location.

Final track reconstruction was performed with the help of the algorithm reading the information from the ANN. Two points were considered to be connected if their interaction made the minimum contribution to the energetic function. Basic problems in this stage are: 1) formulation of conditions of breaking of one track and starting of a new track, if the tracks are located nearly; 2) proper track connection when they are intersected. From this depends the adequate interpretation of the ionogram. Large percentage of errors was introduced in this stage.

After tracing of the tracks, their referencing to specific modes of propagation was required. This is sufficiently complex problem because the technique of referencing strongly depends on a sensing regime and requires special consideration. One of the variants of track identification in case of slant sensing was considered in Ref. 13.

CONCLUSION

The above-considered approach has been implemented as a software package and employed for processing if ionograms of vertical, slant, and return slant sensing of the ionosphere recorded with a sonde with a chirp modulation at the ISTP.[1] As examples, Figs 1–3*b* illustrate the results obtained for ionograms of each types. It took 15–20 s to process one ionogram on a PC IBM 486DX2, depending on the ionogram type.

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