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Feedback neural networks for ARTIST ionogram processing

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Abstract. Modern pattern recognition techniques are applied to achieve high quality automatic processing of Digisonde ionograms. An artificial neural network (ANN) was found to be a promising technique for ionospheric echo tracing. A modified rotor model was tested to construct the Hopfield ANN with the mean field theory updating scheme. Tests of the models against various ionospheric data showed that the modified rotor model gives good results where conventional tracing techniques have difficulties. Use of the ANN made it possible to implement a robust scheme of trace interpretation that considers local trace inclination angles available after ANN completes tracing. The interpretation scheme features a new algorithm for f_oF_1 identification that estimates an α angle for the trace segments in the vicinity of the critical frequency f_oF_1. First results from off-line tests suggest the potential of implementing new operational autoscaling software in the worldwide Digisonde network.

1. Introduction

For many decades the ionosphere as a part of Earth's atmosphere affecting propagation of radio waves was a topic of continuous academic and practical interest. Much effort went into modeling the ionospheric behavior with its dramatic variability as a function of time, location, and solar-terrestrial weather. Practical applications ranging from high-frequency communication to over-the-horizon radar systems require accurate real-time knowledge of the electron density distribution in the ionosphere.

The major input to our understanding of ionospheric plasma conditions came from routine ionospheric sounding. At the current level of ionospheric science and technology, it still offers the most accurate, complete, and cost-effective nowcasting of the media. It has long been recognized that automation of the scaling of ionograms is the critical link in the problem of ionospheric nowcasting. Advances in technology make it possible today to build portable fully automated digital ionosondes like the Digisonde Portable Sounder, or DPS [*Haines,* 1994; *Reinisch et al.,* 1992] for unattended routine observations of the ionosphere. Modern automatic pattern recognition techniques should now be developed to improve the quality and robustness of current ionogram autoscaling techniques.

Since the early 1960s the autoscaling problem has been addressed by a number of ionospheric researchers and specialists in image processing [*Galkin,* 1962; *Mazzetti and Perona,* 1978; *Reinisch et al.,* 1978]. The first operationally successful effort was the development of the Automatic Real Time Ionogram Scaler with True height (ARTIST) by *Reinisch and Huang* [1983] capable of working on-line with digital

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sounders. This paper presents the efforts of developing the next generation of ARTIST software featuring an artificial neural network (ANN) for trace recognition in ionograms and a more robust trace interpretation scheme involving local trace inclination angles obtained by the ANN tracing technique. This software is applicable to both the Digisonde 256 [*Reinisch et al.*, 1989] and the DPS systems operating around the globe. In principle, the software can process any digital ionogram containing sufficient echo information. As a minimum, each range pixel should give the signal amplitudes for both the ordinary and extraordinary wave polarization.

The main goals of automatic ionogram processing and interpretation are to obtain ("scale") a number of important ionospheric parameters, as marked on Figure 1, and to find the leading edge of the traces that are formed by the vertically incident ionospheric echoes. The $h'(f)$ curves thus obtained can then be used to calculate the height profile of electron density distribution. Thus the key tasks in autoscaling are (1) to extract $h'(f)$ curves from the ionogram image and (2) to identify, on the basis of their shape, mutual orientation, and status, the vertical-incidence $h'(f)$ curves corresponding to echoes from the main ionospheric layers. The first part requires design of a pattern rec-

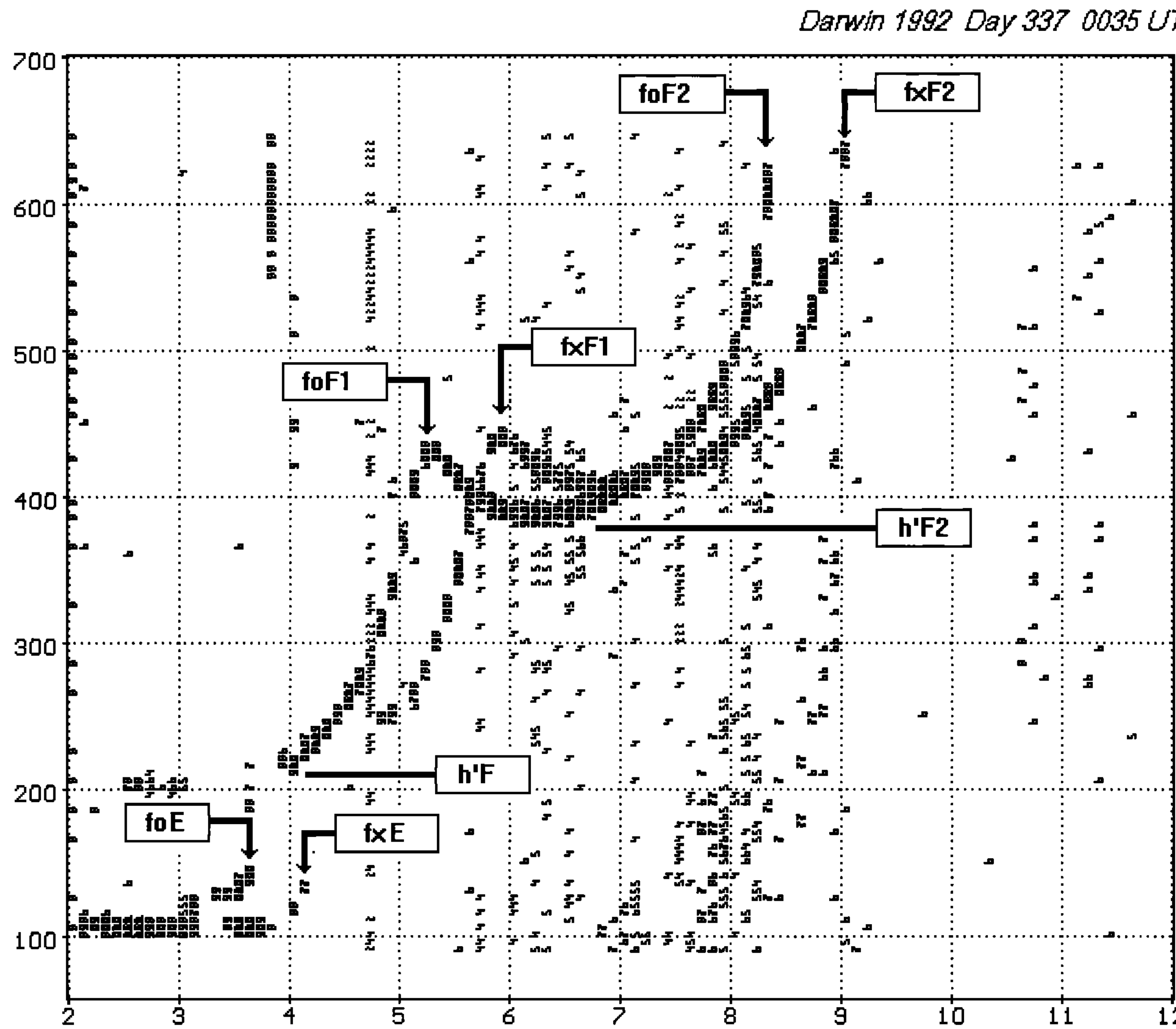


Figure 1. An example Digisonde ionogram, with some of the scaled ionospheric parameters marked.

ognition program; the second part involves an automated linguistic analysis of curves.

2. Extracting $h'(f)$ Curves From Ionogram Image

Following the concept of ARTIST, extracting $h'(f)$ curves starts with identifying ionospheric echo pulses and detecting their leading edges. The recognition task is then reduced to the search of curves in a point pattern; this process is called "tracking." Tracking can be considered as a traditional clustering problem, and a number of algorithms exist that may be considered for the solution of this task. However, complications such as gaps in data (nonauthorized frequency bands, blanketing E_s, etc.), extensive interference and noise, variable number and shape of traces, trace intersections, and steep gradients place insuperable barriers to the traditional approach, which is based on various modifications of the minimum range criterion [e.g., *Murtagh and Rafteri,* 1984]. More powerful techniques like dynamic clustering [*Ioseliani et al.,* 1986] or elastic tracking [*Gyulassy and Harlander,* 1991] impose unacceptable requirements on computer resources. Existing solutions for topside [*Reinisch and Huang,* 1982] and bottomside ionograms autoscaling were based on local recognition techniques [*Reinisch and Huang,* 1983; *Fox and Blundell,* 1989; *Galkin,* 1992] featuring a number of predefined masks optimally fitted to a potential $h'(f)$ curve line. However, the search for more effective techniques is still a pressing task. One approach that combines high capabilities, few constraints, and a reasonable computing time is the use of Hopfield neural networks [*Hopfield,* 1982] with a mean field theory (MFT) updating scheme [*Peterson and Anderson,* 1987] and a good initial neuron configuration to speed up convergence.

2.1. Artificial Neural Networks

Artificial neural networks are an efficient tool replicating some of the human brain functions, such as feature recognition or associative memory [*Durbin and Willshaw,* 1987]. The functionality of ANN varies considerably depending on its configuration and choice of the energy function. Basically, there are two main classes of ANN: feed-forward, or perceptron-like, [*Rosenblatt,* 1958] and feedback [*Peterson and Hartman,* 1989]. The perceptron-like ANN must be first trained on a set of prerecognized patterns, and then it is able to recognize the patterns on its own. Optical character recognition is a typical example of the perceptron-like ANN application. Feedback ANNs are commonly used to solve optimization problems where the ANN can change interdependent factors bringing them to the best agreement.

In contrast to conventional character recognition, the ionogram "alphabet" is more elaborate. Direct presenting of ionogram image parts to a feed-forward ANN is unlikely to train it to recognize the exceptional variety of the trace shapes. Feedback ANNs, however, do not require reduction of trace shapes to a fixed number of patterns; it is the trace model that has to be fixed.

2.2. Feedback ANN for Ionogram Trace Recognition

Figure 2 illustrates the general idea of implementing a feedback ANN to recognize ionogram traces, using the approach suggested by *Peterson* [1990] for track finding in high-energy physics.

The ANN can change direction and length of rotors placed on individual echo points. Initially, all rotors have arbitrary directions; when the optimal arrangement is reached, the rotors are tangential to the curve to be found. This feature of the feedback ANN was achieved by designing its energy function, E, so that it favors rotors aligned to the segment connecting adjacent points (see Figure 3a):

$$E = -\frac{1}{2}\sum_{ij}\frac{1}{|\mathbf{r}_{ij}|^m}\mathbf{v}_i\cdot\mathbf{v}_j - \frac{1}{2}\alpha\sum_{ij}\frac{1}{|\mathbf{r}_{ij}|^m}\left(\mathbf{v}_i\cdot\mathbf{r}_{ij}\right)^2 \qquad (1)$$

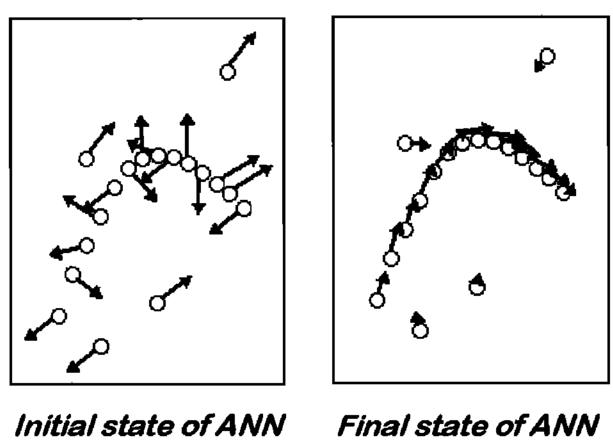


Figure 2. A feed-back optimizing ANN aligning rotors along curve(s).

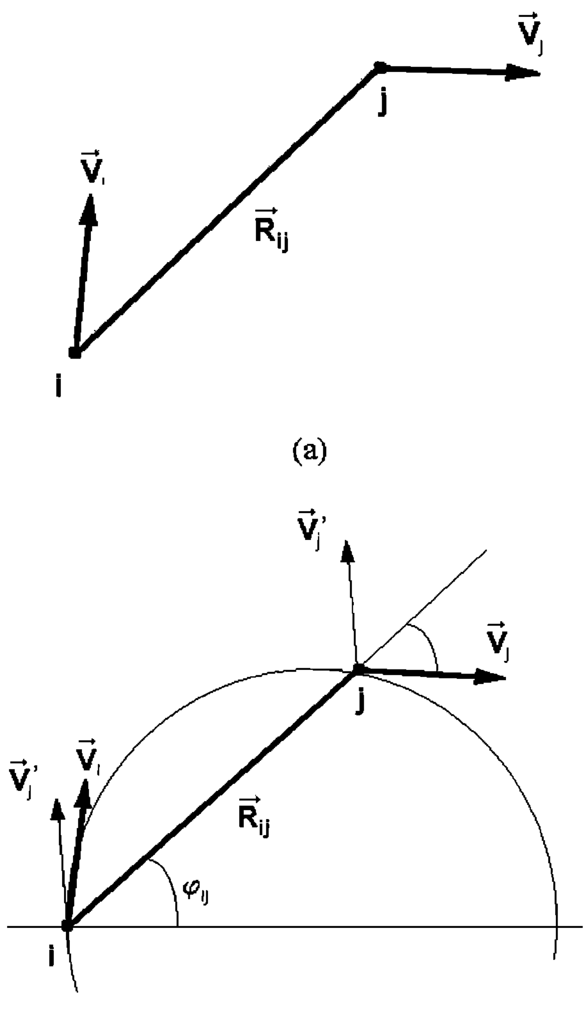


Figure 3. Rotor models for $h'(f)$ curve tracking by ANN. Peterson rotor model (a) and a modified rotor model (b).

The first term in the energy function has a minimum when two rotors $\mathbf{v}_i$ and $\mathbf{v}_j$ have the same direction, the second term has a minimum when the rotor $\mathbf{v}_i$ is aligned with the track segment $\mathbf{r}_{ij}$; α regulates relative contribution of the terms. Thus, at each step of ANN evolution, a rotor changes its direction to a new position where the energy function is smaller. The best possible rotor arrangement corresponds to a straight line, an approach unsuitable for ionogram trace tracking.

Baginyan et al. [1994] have expanded this scheme into a modified rotor model introducing innovations in almost every stage of the ANN algorithm. The original rotor model was modified to accept both circular and linear track segments by placing points on a circle (see Figure 3b) and expressing the energy function as

$$E = -\frac{1}{2}\sum_{ij} \mathbf{v}_i \cdot \mathbf{v}'_j \tag{2}$$

where $\mathbf{v}'_j$ is the mirror reflection of $\mathbf{v}_j$ with respect to $\mathbf{r}_{ij}$ that can be obtained by the following transformation:

$$\mathbf{v}'_j = \begin{pmatrix} \cos 2\phi_{ij} & \sin 2\phi_{ij} \\ \sin 2\phi_{ij} & -\cos 2\phi_{ij} \end{pmatrix} \mathbf{v}_j = W_{ij}\,\mathbf{v}_j \tag{3}$$

The energy function elements are calculated as the angles between $\mathbf{v}_i$ and $\mathbf{v}'_j$. For the same configuration of points i and j, Peterson's rotor model would punish rotors $\mathbf{v}_i$ and $\mathbf{v}_j$ for having nearly opposite directions.

Another modification was made to the evolving scheme itself: the ANN is given an estimate of the track configuration obtained by a more conventional one-dimensional angular histogramming technique (see *Baginyan et al.*, [1994] for details). That brings the ANN close to the optimal solution so that it is no longer necessary to use time-consuming simulated annealing schemes. Instead, an optimally fixed temperature is chosen for the ANN evolving.

One of the advantages of the modified rotor model was the possibility of applying it to the global picture of elementary particle tracks (this is the reason why the expression for the energy function does not contain range factors). However, modeling of ionospheric tracks as circular segments (arcs) can only be done on a local scale. Introducing locality may be achieved without complicating the energy function expression by excluding "far" points from calculations of energy and the ANN evolving procedure. Thus the modified rotor model for ionospheric tracks is supplied with another parameter: an interaction range, ρ.

Expressions (2) and (3) plus a concept for the rotor interaction range determine the process of evolving the feedback ANN. Direction and length of each rotor in the set are updated successively by selecting an interaction area around the rotor and calculating the weighted sum of inputs from the rotors in the selected area:

$$\mathbf{H}_i = \sum_j \mathrm{W}_{ij}\,\mathbf{v}_j \tag{4}$$

Essentially, the vector $\mathbf{H}_i$ is a sum of all contributions from the rotors $\mathbf{v}_j$ in the selected area around rotor i

transposed into the location of the rotor i via expression (3). Instead of accepting $\mathbf{H}_i$ directly as the new orientation of rotor i, the orientation is calculated within the Mean Field Theory [*Peterson and Anderson,* 1987] by applying so-called sigmoid functions to $\mathbf{H}_i$:

$$v_i = \tanh\left(\frac{\mathbf{H}_i}{T}\right) \qquad (5)$$

where T is the optimally selected noise temperature. By distorting the field vector $\mathbf{H}_i$ with (5), a "chaos" is introduced into the ANN dynamics, avoiding capture in a local minimum of the energy function in the search for the global minimum. The MFT emulates the stochastic nature of the chaos by the deterministic equation (5) with the magnitude of the chaos regulated by the temperature T. Neurobiological studies show that the sigmoid function (5) is a rather realistic representation of the nonlinear response of natural neurons to their inputs.

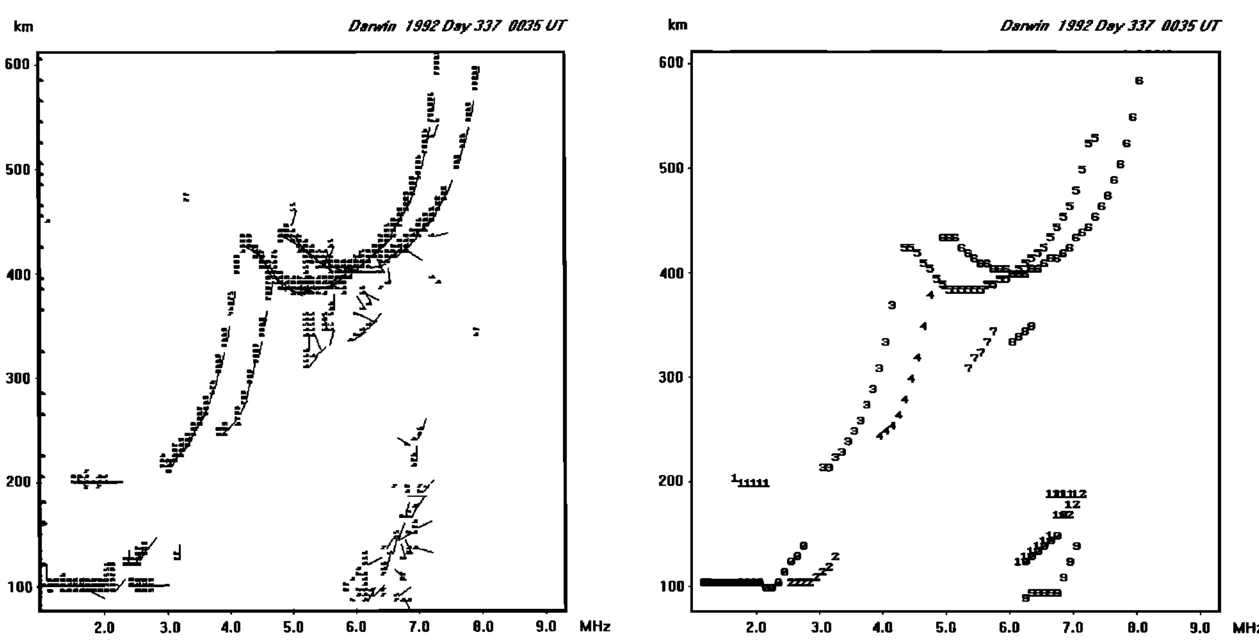
Figure 4a shows an example ionogram where the rotors have been aligned to form tracks. The next step of processing is to optimally link individual rotors together [*Zaznobina et al.,* 1993] and thus form $h'(f)$ curves, as shown in Figure 4b.

2.3. Advantages of ANN

The developed ANN processing algorithm has certain advantages over the tracking schemes traditionally used in ionogram autoscaling. Traditional schemes are unable to reproduce the ability of the human mind to abstract from individual locations of the echo points and see the global picture behind them; they are therefore dangerously sensitive to the "roughness" in the data point sequence.

The idea to fit ionogram traces to expected (calculated) complete trace shapes was first introduced by *Reinisch and Huang* [1983] for the processing of E layer traces. However, the shape of ionogram traces other than the E trace cannot be predicted reliably. Using scaling results of the previous ionogram as the basis for predicting f_oF_2 was suggested by *Wright et al.* [1972] and is used in most scaling algorithms. During fast changes in ionospheric conditions, this approach is not very reliable, especially when only hourly or half-hourly ionograms are made.

A successful attempt to build a smoothing polynomial was made by *Fox and Blundell* [1989]. The polynomial is fitted to 15 already detected echoes to predict location of the next trace point, thus reducing the effect of roughness of the trace line. This tech-



(a) (b)

Figure 4. Results of tracking with the modified rotor model ANN. (a) The optimal rotor orientations are shown. (b) The found $h'(f)$ curves are marked with individual numbers.

nique is still sensitive, however, to "micro" fluctuations of echo locations at the initialization phase, and it also imposes rather strict requirements on the expected shape of the complete trace. A similar approach was suggested by *Voevudskii et al.* [1981].

Hill and Koschmieder [1995] have reported application of a feed-forward neural network, Professional II/Plus, for the recognition of certain ionogram features. Essentially, the neural networks were trained to recognize a short track segment close to the critical frequency; they are then applied to other ionograms so that similar shapes can be found there. In this mode of ANN operation, all input image data propagate through the network in an interdependent manner, so that the importance of individual values is smoothed out. Their ANN works in the schemata-completion mode (classification of novel patterns into predefined categories) and is capable of adopting deviations from the original stored pattern. Unfortunately, the authors observed that even the midlatitude ionograms often posed difficulty for the trained ANN to locate the correct answer. Storing larger segments of tracks in the ANN could be helpful; however, that will induce computational problems and, because of dramatic variability of individual trace shapes, may unacceptably complicate the recognition task.

The optimizing ANN suggested here imposes a rather mild limitation on the local shape of tracks. It does expect locally circular shapes of the track, but that means only that the energy of the ANN will have the absolute minimum if all points engaged in evolving of the network are placed along an arc. If that is not the case, the minimum will still be reached, and that will still happen when all rotors are tangential to the track line regardless of what it actually is. In contrast to other techniques, no circular segments are fitted to the echoes, and no prediction of the next echo location along an arc is made. Also, at each step of evolving, all echoes in the set are engaged in calculations of the new direction and length of a rotor, so that the rotor is affected by an accumulative "smoothed" field from the rest of the echoes and therefore the overall procedure is more robust to microlevel fluctuations.

3. Automatic Interpretation of $h'(f)$ Curves

Each point of the $h'(f)$ curves extracted from an ionogram image (see Figure 4, right panel) contains not only (h', f) coordinates but also the corresponding ionospheric echo status (amplitude, polarization, angle of arrival, Doppler shift) and rotor direction and length. Echo status is very important information for correct identification of trace data; the rotor direction provides a reliable estimate of the local inclination of $h'(f)$ curves. This is the most complete data set ever presented to an ionogram autoscaler.

The following section describes the current state of the new ANN-ARTIST project. Dubbed ARTIST-B, the algorithms have retained ARTIST's capability to handle disturbed and nonstandard ionospheric situations that is based on the experience gained in the worldwide Digisonde network over the past 15 years. ARTIST-B includes the use of the trace inclination, a feature developed by *Galkin* [1992] for the Program for Autoscaling of Conventional Ionograms with a Flexible Interpretation Control (PACIFIC) interpretation scheme. This feature makes the trace identification routine more reliable. Using the PACIFIC order of ionogram analysis indicated in Figure 5, that is, the sequence E, F center, E_s, f_xF_2, etc., makes the ARTIST-B approach noticeably different from the conventional "reading" of ionograms from left to right [e.g., *Galkin and Dvinskikh*, 1968; *Fox and Blundell*, 1989].

3.1. Scaling Critical Frequencies of the F_2 Layer

The first three steps of interpretation (see Figure 5) are analogous to the ARTIST scheme [*Tang et al.*, 1988]. Then, the upward inclined curve segments close to the F_2 center are used as the starting landmarks for retracing F_2 layer data, unlike the F_2 center itself used by ARTIST. The same idea to trace F_2 layer data starting from the critical frequencies (i.e., from the right to the left) was suggested independently

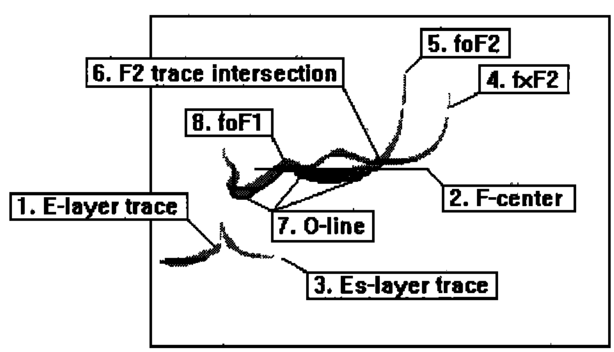


Figure 5. PACIFIC interpretation scheme designed for ionograms without polarization tags.

by *Yosida* [1989] and *Minullin et al.* [1989] but with different landmark search procedures.

Proper selection of upward inclined track segments corresponding to cusps in the F_2 region becomes very important in case of a disturbed ionosphere producing several F_2 traces. The selection may present a difficulty even for a human operator and generally requires analysis of an ionogram series to identify traces that belong to different stratifications possibly caused by traveling ionospheric disturbances activity (off-vertical traces are excluded as they are tagged by status marks). Spread F conditions present a special case with a sum of interfering traces, and a vertical incidence trace may or may not exist. In any case, possible absence of the upward inclined part of the trace due to weak echoes in the vicinity of the F region cusp should be taken into account. These considerations were formally expressed in terms of logical steps providing selection of the inclined parts of the ionogram traces in the vicinity of the critical frequency f_oF_2. A bounded search area is defined, the location and size of which are variable depending on the F_2 center height, the last frequency containing O echoes [*Mazzetti and Perona,* 1978], spread F characteristics, and the shape of the $2xF_2$ trace.

Even with the capabilities of neural network processing, the echoes close to the critical frequency are sometimes not traced up to the cusp, and the existing ARTIST hyperbola-fitting routine was retained for the determination of the critical frequencies. The current ARTIST simultaneously fits O hyperbola and X hyperbola that are offset by half the gyrofrequency in the frequency direction. This may result in inaccurate X hyperbola fit when the O and X cusps have different heights. ARTIST-B fits the hyperbolas separately and then checks if they are compatible with each other. Experience showed that the joint hyperbolic fit is rather sensitive to deviations from the model, so the separate fit increases the chance of obtaining at least one cusp shape correctly and restoring the other one by shifting and fitting it to the remainder of the trace.

3.2. *O* Line Detection

After both hyperbolas are obtained, they are matched to the $h'(f)$ curve segments that were used for hyperbolic fitting and "retraced" backward to the point where they intersect (see Figure 5). Then, the $h'(f)$ curve consisting of O echoes between the intersection point and f_oE (so-called "O line") is constructed.

3.3. Scaling Critical Frequency of the F_1 Layer

The critical frequency of the F_1 layer, f_oF_1, is indicated as an inflection point or a cusp of the O line. To make sure that a maximum of the $h'(f)$ curve is distinguished enough to declare it f_oF_1, straight lines are fitted to the line on both sides of the point of interest (see Figure 6), and the angle between them, known as α angle of the F_1 cusp [*Shchepkin and Vinitsky,* 1982], is checked against a station-dependent control value. In case several extrema of the O line are found, the one is chosen which is the closest to the long-term prediction value of f_oF_1.

3.4. First Results of ARTIST-B

The interpretation scheme designed for autoscaling of Digisonde ionograms was implemented in the ARTIST-B program. Plate 1 presents an example of autoscaling an ionogram obtained by the DPS on December 2, 1992, 0135 UT (1035 MLT) at Darwin, Australia during quiet ionospheric conditions. The rectangle painted in sky blue shows the area selected for the search of the $h'(f)$ curve segment corresponding to the X cusp of the F_2 trace. Black circles indicate the best hyperbola fit to the cusp, and a short black horizontal line is drawn at the height level where the model hyperbola still contains echo points (a measure of the fit quality). The gray rectangle outlines the area selected for the search of the f_oF_2 cusp. Again, black circles and a horizontal line show the results of the O hyperbola fit. Yellow squares on the black background correspond to the O line. Three O line points were identified as possible F_1 signatures.

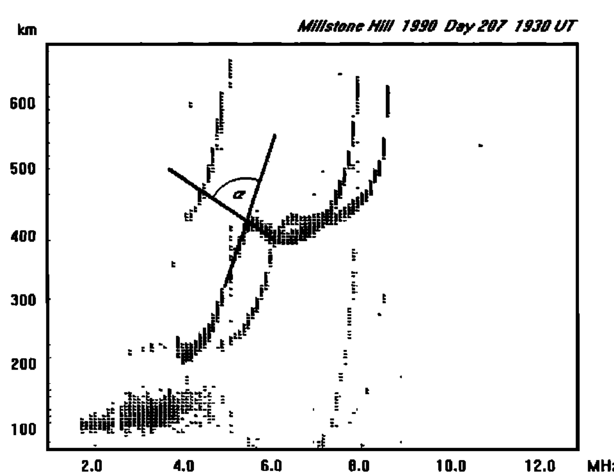


Figure 6. The α angle of the F_1 trace.

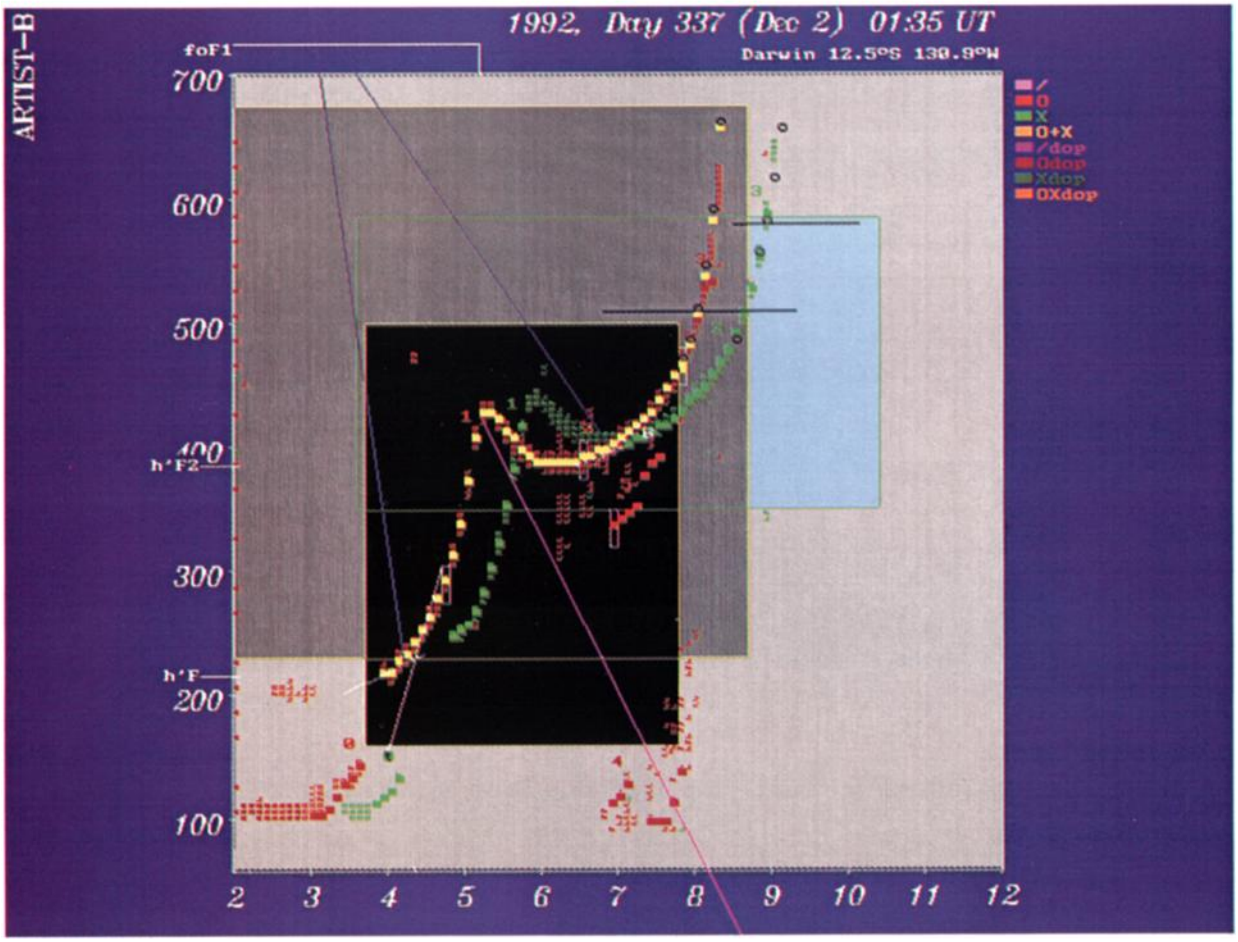


Plate 1. ARTIST-B autoscaling example.

They are identified by two violet pointers coming from above (inflection points) and one pointer from below (cusp point). The algorithm for evaluation of the α angle of the F_1 cusp has made fits of linear segments (white) to both inflection points, and both angles are found to be too large. The cusp of the *O* line is then identified as the critical frequency of the F_1 layer.

Plate 2 presents an example of autoscaling during spread *F* conditions at Millstone Hill on May 7, 1993, 0614 UT (0114 MLT). ARTIST-B identified the correct *O* trace (yellow rectangles).

4. Summary

The paper presents the current state of the ongoing pilot project ARTIST-B, whose main objective is to apply artificial neural networks to ionogram trace recognition. An ANN-based algorithm for tracking *h'(f)* curves on ionograms has been designed and implemented. It uses a feedback optimization ANN with an MFT updating scheme and a modified rotor model of ionogram *h'(f)* curves. The new *h'(f)* tracking technique made it possible to upgrade the existing ARTIST interpretation scheme. Preliminary results indicate improved autoscaling during disturbed ionospheric conditions, suggesting that an operational ARTIST-B version could be developed, tested, and distributed to the worldwide Digisonde network [*Reinisch,* 1995].

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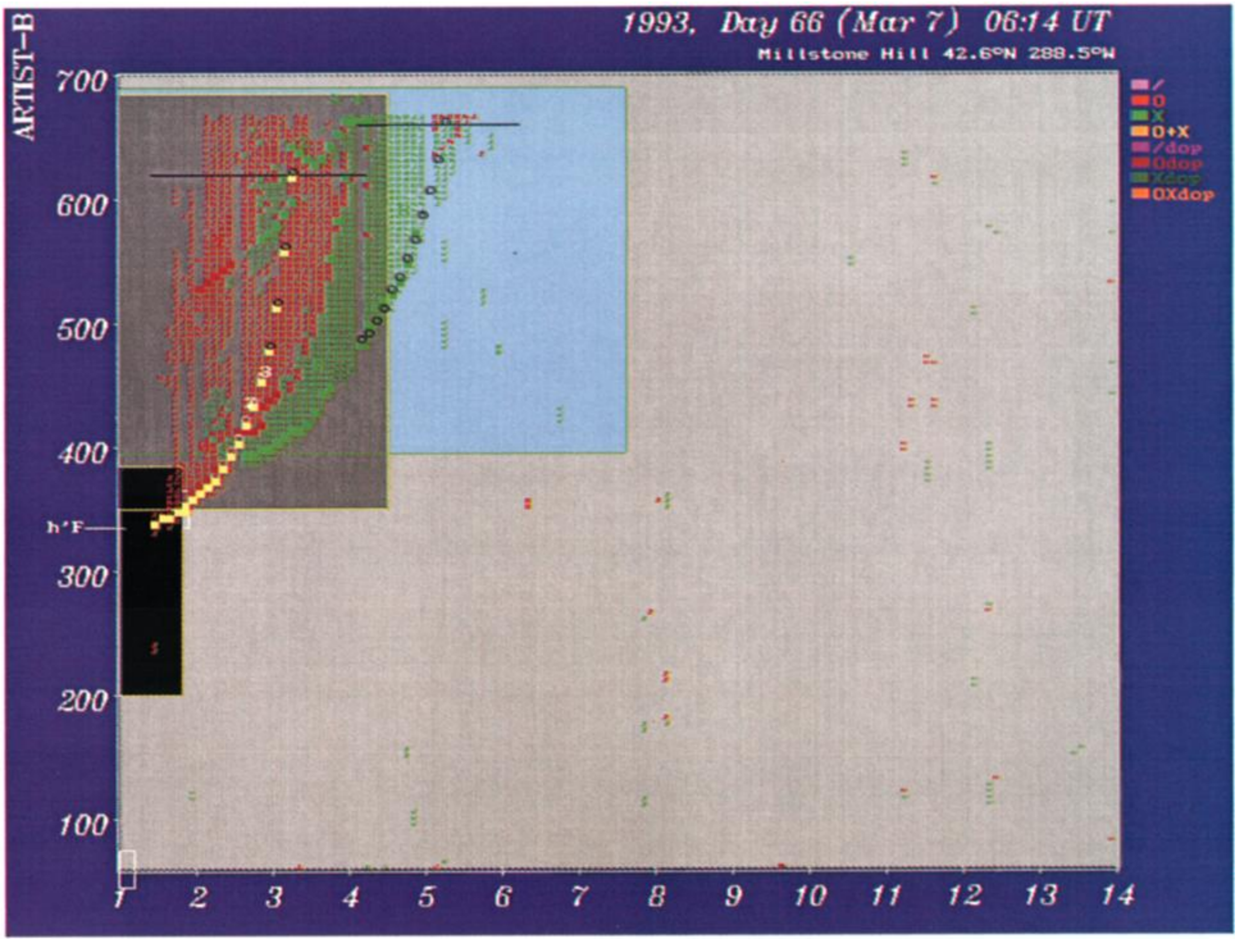

Plate 2. Scaling of an ionogram obtained under spread *F* conditions.

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