NEURAL NETWORKS MODELS IN THE INVERSION OF MULTIDIMENTIONAL IONOGRAMS

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ABSTRACT

Modern sounding systems are able to measure multidimentional backscatter ionograms (MBI). These ionograms represent the propagation delay time (Tg) and the Doppler frequency shift (Fd) against the elevation angle (β) of the sounding wave and the sounding frequency (Fe). In this paper, we address the MBI inversion issue. More precisely, we investigate the extraction of the model ionospheric parameters from which MBI are derived, with techniques combining data fusion with Multi-Layer feedforward neural networks. This work aims at recovering the parametrized geographical distribution of the ionospheric parameters in a large circular area around the sounder. The experiments have been carried out using MBI simulated with the Chiu model of ionisation for a single Chapman layer. Better results are achieved when a hierarchical network is used to invert the merged MBI, compared with a direct inversion using a large network, dropping the average percentage error on the whole area down to 7%. This demonstrates the ability of neural networks to produce information that would otherwise be unvailable.

1. INTRODUCTION

The method of sky-wave backscatter sounding, developped a long time ago [1][2], consists of receiving obliquely transmitted HF energy from distant ground backscatter. The received clutter shows the radiowaves that propagate from the sounder, are refracted by the ionosphere, undergo backscatter from the Earth's surface and eventually return to the sounder after a second ionospheric refraction. When the radiowave's frequency (Fe) varies in a discrete set, the corresponding clutters form together the backscatter ionogram (BI), e.g the group path as a function of Fe. These measures aim at recovering the parameters of the electron density profile. For this research, the higher ionospheric layer (F2 layer) is of major interest. Its parameters are the critical frequency f_{oF2}, the altitude of maximum electron density h_{mF2}, and the semi-thickness of layer y_{mF2}. The inversion problem focalizes on determining the triplet (f_{oF2}, h_{mF2}, y_{mF2}) from a simple BI. A classical approach for solving the BI inversion consists in using the minimum group delay frequency characteristic (GFC), that is, the leading edge of the BI as input data [3]. Although the BI is easy to obtain, it produces a cumbersome inversion problem. As there exist noise and errors in the measurements , a direct inversion from the GFC gives many instable solutions. Indeed, even if noise is absent, the mapping between the GFC and the ionospheric parameters is non-bijective. In other words, two similar GFC can represent two very different configurations (f_{oF2}, h_{mF2}, y_{mF2}). Several numerical methods have been developped to derive steady solutions[4]. Most authors use perturbation methods that consist of adjusting synthetic BI computed by raytracing to measured BI. The error is computed in order to correct the electron density parameters f_{oF2}, h_{mF2}, y_{mF2} that govern the ray tracing process. To reach a single solution, constraints on the solution (and its derivatives) are commonly imposed to the cost function to minimize. This largely used approach leads to reasonable results on simulated data but implies substantial computational costs for accurate ionospheric models. An original approach was investigated in [8], using data fusion and neural networks techniques. The results are probant on simulated ionograms, but the method requires a set of independent sensors, and two synchronized sounding stations.

In this paper, we propose to solve the inverse problem by an original approach in which the measurements are processed from a single station, in such a way that the mapping can be directly inverted. We start from the Delay-Doppler Function (DDF), which represents the Doppler frequency shift (Fd) and the group delay (Tg), at a fixed radiowave sounding frequency Fe (figure 1). We are now at a period when the technology allows us to precisely measure the elevation angles β of backscattered rays impinging on the receiving antenna. With this additional information, we can construct a three-dimensional DDF, and in such a way, we hope to get a unique solution to the inverse problem. Besides, we expect this solution to be less sensitive to the noise on the input data. Moreover, in order to cover all the daily configurations of the electron density profile, the BI is measured for several sounding frequencies Fe. Collecting the BI for varying Fe provides a multi-dimensional backscatter ionogram (MBI), representing more preciselythe ionosphere. The objective of our study is to go further than assessing the ionospheric parameters at one remote geographical point. Instead, we will estimate a model which represents the distribution of these parameters in a circular area ranging over 3000 km around the sounder. The critirium used to measure the performance is the average of the maximum relative absolute error (MRAE) on a grid of geographical points in the sounding area.

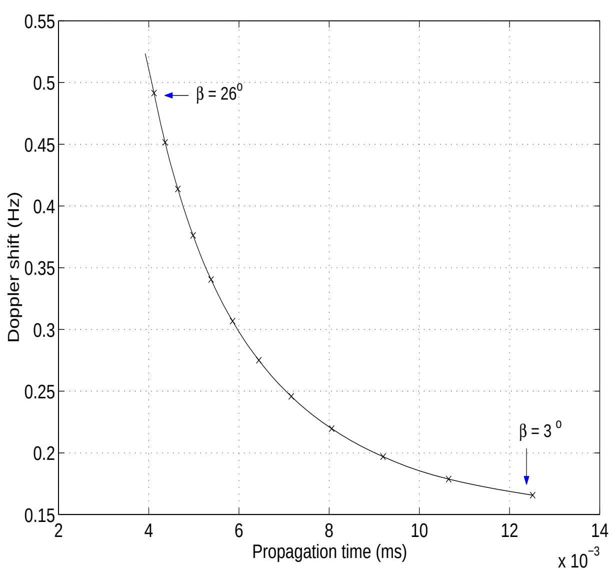

Figure 1: Example of Delay-Doppler function for 12 elevation angles

2. INVERSION OF IONOGRAMS

For the purpose of this research, rather than real ionograms, synthetic ones are produced by a ray tracing software written in our department, which generates a MBI assuming that the ionosphere is spherically stratified, and that the Earth's magnetic field and the collisions are negligible. This software simulates the ionosphere under variable conditions. These ones can be used to label the data, hence allowing to use supervised networks such as the standard backpropagation multi layer perceptron.

2.1. Processing of inputs and outputs

Since MBI are multi-dimensional plots, they have to be reduced to a low size vector before they can be used as input for a neural network. Indeed, smaller networks learn faster and reach lower mean square error, at the condition that the input coding is sufficiently discriminant. Several studies [9] permit to determine the range of the sounding frequencies Fe and of elevation angles β that produce efficient MBI and exibiting concise features. Hence, it seems that 90 points MBI are effective, these points being derived from DDF simulated for 6 sounding frequencies, 5 elevation angles and a fixed azimuth.

The backscatter sounding from a single site allows to collect informations about the remote ionosphere in all azimuths. Using this advantage, we ambition to estimate the local geographical distribution of the plasma frequency f_{oF2} parameter. In that case, the input vector will consist in the fusion of MBI computed for eight azimuths equally spaced that range over 360 degrees. In order to simulate the behaviour of the f_{oF2} parameter, the phenomenological Chiu model [5] has proved to be usefull in generating samples for a circular geographical area ranging over 3000 km around the sounder. To simplify the inverse problem, we have to reduce the number of parameters as many as possible. Hence, local ionospheric parameter distribution is represented in a concise form by means of a simple model that matches the geographical variation of electron distribution. The central position of the sounder in the sensing zone, suggests the use of polar geographical coordinates (range, azimuth) instead of cartesian coordinates (latitude, longitude). Then, a grid of values of the set (f_{oF2}, h_{mF2}, y_{mF2}) is computed for discrete ranges and azimuths. A study of these samples, when varying the local time, the day of the year and the monthly smoothed Zurich relative sunspot number, shows that range influence can be properly described by a polynomial, while azimuth effects can be accurately represented by a trigonometric function (limited Fourier series). Using these remarks, we propose the following model for ionospheric parameters f:

$$f(\rho, \phi) \quad = \quad f_{00} + a_1(\phi)\,\rho + a_2(\phi)\,\rho^2 + a_3(\phi)\,\rho^3$$

$$a_i(\phi) = \sum_{k=0}^{3} a_{i,k}\cos(k\phi) + b_{i,k}\sin(k\phi), \quad i = 1,2,3$$

f_{00} is the parameter value obtained from a vertical sounding. The synthetic form of this model reduces the number of parameters to be estimated by the networks.

2.2. Training and testing data

Five thousand MBI were generated by our software, for various quiet ionospheric configurations. These configurations, take into account the local time, the day of the year and the monthly smoothed Zurich relative sunspot number, but not all combinations of these parameters will occur in practice. So, invalid combinations can produce irregular, or even blank MBI. This is why these MBI were sorted out to remove any that were invalid. The remaining 4840 MBI were then randomly splited into two sets, one for training and one for testing.

2.3. Neural network design

We selected the RPROP algorithm [6] to train the networks, since in our previous experiments it allowed to reduce network error faster and to a lower value than other optimization algorithms. From now on, the main difficulty remains the selection of a suitable neural architecture for inverting the multi-azimuth MBI (MAMBI), resulting of the fusion of single-azimuth MBI. The task consists in assessing the twenty four parameters $a_{i,k}$ and $b_{i,k}$ starting from the MAMBI. Previous experiments have shown that a single large multilayer perceptron architecture couldn't succeed in reaching low accuracy on the estimation of the ionospheric parameters. Indeed, a task with too many inputs and outputs often leads neural network models to poor performance, due to numerous local minima and slow convergence. As a consequence, we decide to divide this crude inversion into small tractable problems, each solved by low-size neural networks. In that way, the MBI contained in the MAMBI are merged to provide four input vectors, each of them, concatenates the information of two opposite azimuths. Four networks were trained to estimate the polynomial parameters fiting the diametral range evolution for each of the four directions. The four multilayers perceptrons with the following design (126:40:10:4), are trained independently. Then, a fifth (16:40:40:24) network, fuses the outputs calculated by the four previous networks to produce the 24 parameters describing the local ionospheric distribution. Figure 2 describes the structure of the networks that were trained in the course of this research. MBI-1 up to MBI-4, are the merged MBI corresponding to the four directions.

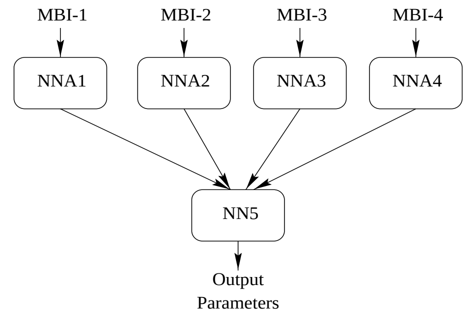

Figure 2: Fusion of MBI using Multilayer Neural networks

The performance of the neural modular structure is reported in figure 3. This plot shows the cumulative histogram of the average maximum relative absolute error over the testing examples. With this representation, we can see directly the percentage of ionospheric configurations accuratly estimated. We can point out the quite reasonnable accuracy (7% of relative absolute error) in 90% of cases, knowing that the entire ionospheric distribution is considered here. Clearly, testing numerous different architectures in the neural modular system is prohibitive, but forthcoming results where cooperation between neural nets is used, are promising. In this method, all the neural nets are trained simultaneously, providing a more accurate model.

3. CONCLUSION AND DISCUSSION

This work demonstrates the capabilities of the MBI direct inversion technique as an accurate and stable tool for determining the local geographical distribution in an ionosphere modeled by a single F2 layer. To our knowledge, none other simulated techniques employed for ionospheric measurements, investigate the space distribution of the three parameters of the F2 layer over a large geographic area. Our results are promising, even if they are obtained from a first simple ionospheric model and not from real data. Actually, the real ionosphere is composed of several layers and exhibits geographical variations causing horizontal gradients of ionization. Some authors [7] have considered the horizontal ionization gradients in their models. It appears very important to assess these gradients as they always exist in real ionosphere. These gradients can be seen as the first order momemtum of the local distribution of F2 layer. In that sense, our investigations allow to go further since we can derive the distribution of all the F2 layer parameters with a reasonable

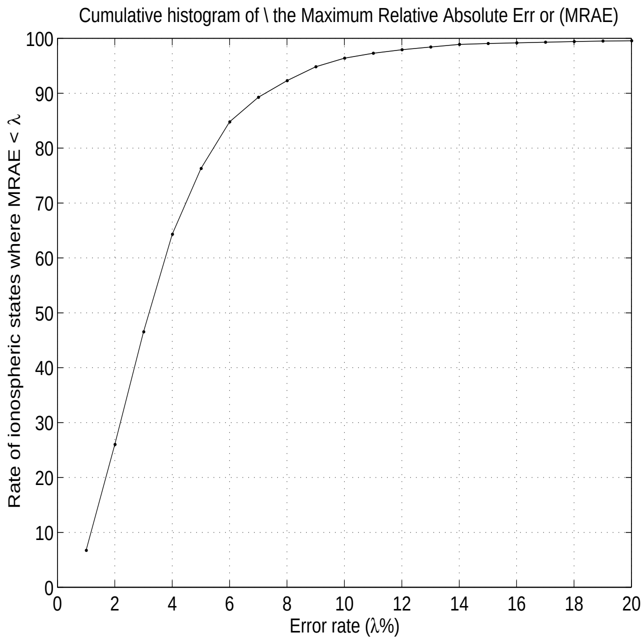

Figure 3: Cumulative histogram of the Average Maximum Relative Absolute Error (MRAE)

error rate, within a wide circular area centered on the sounder.

4. REFERENCES

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