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Modes of radiowave propagation : neural learning

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Abstract : Modes of radiowave propagation depends upon the radiorefractivity gradient of the medium through which it is propagating. Radiosonde data collected from Dum-Dum Airport, Kolkata is analysed to calculate the radiorefractivity gradient. The estimated value can be divided into four categories namely subrefraction, normal refraction, superrefraction and ducting. In this paper, we have used a multilayer perceptron (MLP) to learn the relationship between atmospheric parameters (T, P, e *etc*) and the output classes which helps in predicting the mode of radiowave propagation. Studies have been made using different network topologies. The results are presented for various number of hidden layers and nodes, using different size of training sets. The trained network is used for subsequent rule generation.

Keywords : Electromagneticwave propagation, radiorefractivity, multilayer perceptron (MLP).

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1. Introduction

Tropospheric radiowave propagation is one of the important areas in the field of electronic communication sciences. Radiorefractivity $N(T, P, e, h)$ and the radiorefractivity gradient ΔN are the key parameters to estimate the mode of radiowave propagation, where T, P, e and h denote the temperature, pressure, vapour pressure and height respectively (of the tropospheric region). The radiorefractivity gradient ΔN can be divided into four basic intervals defined as (i) $0 \geq \Delta N \geq -40$, (ii) $-40 \geq \Delta N \geq -75$, (iii) $-75 \geq \Delta N \geq 157$ and (iv) $\Delta N < -157$.

If the estimated ΔN is lying in interval 1 the mode of radiowave propagation is said to be *subrefracted*. Under this mode of propagation the signal level at the receiver site experiences a greater loss and sometimes it becomes too small to use. The mode of radiowave propagation is said to be *normal* if ΔN lies in interval 2. In the presence of normal refractive condition radiowave travels between a pair of transmitting and receiving antennas with moderate path loss. On the other hand, if ΔN lies in the interval 3 or 4 the mode of radiowave propagation is termed as *superrefraction* or *ducting* respectively. On the occurrence of superefraction and duct condition the radiowave between a pair of transmitting and receiving antennas propagate with least path loss which, in turn, improves the reliability and the performance of the system.

Artificial neural networks (ANNs) attempt to replicate the *computational* power (low-level arithmetic processing ability) of biological neural networks and, thereby, hopefully endow machines with some of the (higher-level) *cognitive abilities* that biological organisms possess (due in part, perhaps, to their low-level computational prowess). However, an impediment to a more widespread acceptance of ANNs is the absence of a capability to explain to the user, in a human-comprehensible form, how the network arrives at a particular decision. Recently there has been widespread activity aimed at redressing this situation, by extracting the embedded knowledge in trained ANNs in the form of symbolic rules [1,2]. This serves to identify the attributes that either individually or in a combination, are the most significant determinants of the decision or classification.

In our present investigation, we have used a multilayer perceptron (MLP) and its fuzzy version (fuzzy MLP) to learn the relationship between the input parameters T, P, e, h, T_s, e_s, h_s, N and the output class ΔN. The four intervals for ΔN are mapped to three output classes, clubbing intervals 3, 4 to class 3 only. This helps us in predicting the mode of radiowave propagation from the measure of T, P, e of the

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tropospheric region at a particular height h. Studies have been made using different network topologies. The learning rate is gradually decreased. Extensive results are presented for various numbers of hidden layers and nodes, using different sizes of training sets. The trained network is used for subsequent rule generation.

2. Rule generation and fuzzy MLP

In general, the primary input to a connectionist rule generation algorithm is a representation of the trained ANN, in terms of its nodes and links, and sometimes the data set. One interprets one or more hidden and output units into rules, which may later be combined and simplified to arrive at a more comprehensible rule set. These rules can also provide new insights into the application domain. The use of ANN helps in (i) incorporating parallelism and (ii) tackling optimization problems in the data domain. Fuzzy neural networks [1] can be used for the same purpose, and can also handle uncertainty at various stages.

The fuzzy MLP [1] incorporates fuzziness at the input and output levels of the MLP, and is capable of handling exact (numerical) and/or inexact (linguistic) forms of input data. Any input feature value is described in terms of some combination of membership values in the linguistic property sets *low* (L), *medium* (M) and *high* (H). During training, the weights are updated by backpropagating errors.

An n-dimensional pattern $F_i = [F_{i1}, F_{i2}, ..., F_{in}]$ is represented as a $3n$-dimensional vector

$$F_i = [\mu_{\text{low}}(F_{i1})\ (F_i), ..., \mu_{\text{high}}\ (F_{in})\ (F_i)], \qquad (1)$$

where the μ values indicate the membership functions of the corresponding linguistic π-sets *low*, *medium* and *high* along each feature axis.

The network is trained using backpropagation and the connection weights pruned with weight decay. The trained network is next analyzed for rule generation. The strong paths from the output nodes (classes) to the input (features), *i.e.*, those paths having large magnitude, are extracted. We consider both positive and negative link weights in the process. The antecedents of the rules are in terms of the linguistic values at the input to which the path can be traced.

3. Results

The algorithm was implemented on the radiosonde data of the pre-monsoon season collected from Indian Meteorological Department, Kolkata and consisted of 360 patterns points. There were eight features corresponding to temperature (T), pressure (P), vapour pressure (e), height (h), surface temperature (T_s), surface vapour pressure (e_s), height at 1000 mb pressure level (h_s) and radiorefractivity (N). The three output classes refer to sub-refraction, normal refraction and super-refraction and ducting. The input features were split into 24 components in the linguistic space of eq. (1).

Various three-layered networks (MLP and fuzzy MLP) were used with different numbers of hidden nodes and training sets. Tables 1 and 2 provide sample classification results using the MLP with 30% training set and the fuzzy MLP with 40% training set respectively.

Table 1. Recognition score for MLP with 30% training set.

No. of hidden nodes	Training set Class 1	Training set Class 2	Training set Class 3	Training set net	Testing set Class 1	Testing set Class 2	Testing set Class 3	Testing set net	Mean square error	No. of iterations
2	96.77	86.21	84.34	88.79	89.61	76.71	65.45	80.56	0.0701	2301
3	100.00	85.71	98.72	86.92	85.71	74.66	66.82	77.46	0.0654	2251
4	93.33	85.71	98.72	90.65	90.91	70.55	63.64	78.31	0.0561	2301
5	100.00	92.86	98.72	93.46	87.01	73.29	60.00	77.18	0.0439	2251
6	100.00	100.00	98.72	97.20	87.66	69.86	61.82	76.34	0.0324	2251

Table 2. Recognition score for fuzzy MLP with 40% training set.

No. of hidden nodes	Training set Class 1	Training set Class 2	Training set Class 3	Training set net	Testing set Class 1	Testing set Class 2	Testing set Class 3	Testing set net	Mean square error	No. of iterations
2	93.55	91.38	86.36	91.55	75.97	60.27	50.91	65.63	0.0630	1901
3	96.77	87.93	81.82	90.85	80.52	63.01	54.55	69.30	0.0753	1951
4	100.00	100.00	86.36	97.89	83.12	71.23	52.73	73.52	0.0417	1951
5	100.00	98.28	90.91	97.89	85.06	67.81	50.91	72.68	0.0314	1951
6	100.00	100.00	90.91	98.59	78.57	66.44	54.55	69.86	0.0246	1951
7	100.00	100.00	90.91	98.59	80.52	71.23	58.18	73.24	0.0231	1951
8	100.00	100.00	95.45	99.30	77.92	69.18	52.73	70.42	0.0238	1951
9	100.00	100.00	95.50	99.30	81.17	70.55	49.09	71.83	0.0202	1951
10	100.00	100.00	90.91	98.59	77.92	74.66	50.91	72.39	0.0177	1951
11	100.00	100.00	90.91	98.59	81.17	71.92	54.55	73.24	0.0190	1951
12	100.00	100.00	90.91	98.59	84.92	70.55	52.73	73.80	0.0195	1951

Sample rules extracted from a pruned fuzzy MLP, with four hidden nodes, for class 1 (sub-refractive) are as follows.

Positive : If e is *high*, H_{1000} is *high* or *medium*, T is *low*, T_s is *low*;

Negative : H is *not high*.

4. Conclusions

We have demonstrated classification and rule generation for radio-sonde data using an MLP and fuzzy MLP. The networks learnt the relationship between the input parameters T, P, e, h and the output class ΔN. Studies have been made using different network topologies. It is expected that this type of neural network based model will be advantageous to the scientists and engineers working in the area of remote sensing, atmospheric science, radio communication and various other related fields.

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