S.1.6 Recurrent Self-Organizing Map for Lightning Density Patterns Recognition

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Patterns Recognition over the Brazilian Amazon, which may be used in monitoring control and mitigation of the lightning risks and damages associated. In this context, the lightning density patterns recognition for the Amazon region may be used with subsidiary element in decision-making regarding preventive actions to avoid further damage to the electrical system. The outages lead to productivity and information losses in the industrial production processes, which contribute negatively to the composition of the electric power quality indices. This work analyzed the capacity of the Recurrent Self-Organizing Map (RSOM) for clustering and classification of lightning density in order to contribute with the monitoring control over the Brazilian Amazon. The option of using this type of neural network was due to the fact that it uses only the input parameters, making it ideal for problems where the patterns are unknown. In summary, with the RSOM algorithm it was possible to evaluate the usefulness of these recurrent neural networks for the lightning density patterns recognition.

Keywords—Neural Networks; Recurrent Self-Organizing Map; Lightning Density; Patterns Recognition; Brazilian Amazon. I. INTRODUCTION The Lightning Density Patterns Recognition is very important for monitoring and control of the lightning risks. In especial for Amazon region, the lightning density patterns recognition is strategic due to the possibility of using it as subsidiary element in decision-making regarding preventive actions to avoid further damage to the electrical system. This study aimed to evaluate the capacity of the Self-Organizing Map (SOM) [1], [2] and its temporal extension known as Recurrent Self-Organizing Map [3]—[6] for clustering and classification of the daily lightning density in order to contribute with the patterns recognition studies over the Brazilian Amazon.

II. SOM AND RSOM A. Self-Organizing Map (SOM) The SOM is a nonlinear algorithm used for data clustering and classification. This algorithm is characterized by the processing of static data, i.e., not considering the data timelines, with the output of this neural network dependent only on present input data [1], [2]. The SOM is a single-layer neural network, in which it is recorded the learning by algorithm. This layer usually has low dimension structure (1D or 2D). The training of the SOM is based on unsupervised learning, by adjusting of prototypes, according to the distribution of the input data, performed as follows: The weight vector of each unit in the map space is compared to an input vector. A metric-based criterion is chosen to determine the unit that has the minimum distance (Best Matching Unit), i.e., the neuron with the most similar prototype is selected as winner or winning unit. The neurons of the SOM cooperate to receive future incoming stimuli in an organized manner around the winner neuron. The winner neuron will be the center of a topological neighbourhood where neurons help each other to receive input signals along the iterations of network training. Thus, after obtaining the winning neuron, its weights are adjusted to increase the similarity with the input vector, the same being done for the weights of its neighbours, by an update rule. The neural network decreases its ability to learn, gradually over time, in order to prevent the drastic change by new data, in the sedimented knowledge through several iterations. The time constant influences the network learning as follows: high value generates long period of intensive learning. The neighbourhood function in a SOM is a similar way to reproduce the interactions of biological neurons, which stimulate their neighbours, in decreasing order, by increasing the lateral distance between them. So, for the SOM, this feature is reproduced by the parameter that determines how each neuron will receive readjustment to gain the future input stimuli. The largest adjustments are applied to the winner neuron and its neighbours, and minors to the neurons further from the winner neuron, because this parameter decreases with increasing lateral distance. Normally it is used the Gaussian function to represent the rate of cooperation between the neurons. Considering that the effective width of the topological neighbourhood will diminish with time increasingly specialized network regions will be built for certain input patterns. Over the course of iterations the radius of a neighbourhood should be smaller, which implies lower values, over time, thereby resulting in a restricted and specialized neighbourhood. B. Recurrent Self-Organizing Map (RSOM) The SOM was originally designed for the static data processing, but for the dynamic data patterns recognition, it becomes necessary to include the temporal dimension in this algorithm. An algorithm that introduced the temporal processing to the SOM was the Recurrent Self-Organizing Map (RSOM) using a new form of selection of the winner neuron and weights update rule [3]—[6]. This algorithm applies a leaky integrator from the unit outputs into the inputs. The RSOM allows storing information in the map units (difference vectors), considering the past input vectors. Thus, the RSOM takes into account the past inputs and also starts to remember explicitly the space-time patterns. The basic differences between RSOM and SOM networks are: For the determination of the winner neurons in RSOM is necessary to calculate and record the recursive difference, while in SOM the choice criterion of the winner neurons is the quantization error; The winner neuron in RSOM is one with smallest recursive difference, while in SOM is one with smallest quantization error. III. MATERIALS AND METHODS A. Study Area and Lightning Data Set The study used daily lightning density maps with grid 1-degree by 1-degree resolution, in the Brazilian Amazon, between latitudes: 1° S and 7° S and between longitudes: 48° O and 54° O (36 pixels or 36 sub-areas), created starting from the STARNET (Sferics Timing and Ranging Network) database, on the data collected during the rainy season of the year 2011. Figure 1 shows the square study area with vertices A, B, C and D. Fig. 1. Square study area with vertices A, B, C and D. B. Clusters formation for evaluation of the models In evaluation of the applicability of SOM and RSOM for the Lightning Density Patterns Recognition, clusters were built using the K-means technique, which generated starting from 120 instances, two clusters containing 35 and 85 examples, for the cluster 1 and 2, respectively. Figure 2 shows the Survey Plot of the two clusters. For the 120 days analyzed, Cluster 1 has the lightning highest frequencies, per pixel, while the Cluster 2 has the lightning lowest frequencies. Fig. 2. Survey Plot of the Cluster 1 (blue) and Cluster 2 (red). C. Training and evaluation of the models For the performance analysis of the networks (SOM and RSOM) 1 map was constructed, for each network type, in the grid 6 x 6 units, therefore 2 maps in total. Each network was trained with 40 examples extracted of the data set, with 20 examples of each cluster, randomly chosen. After training, the units of the maps were labeled according to their winning histories during training. This allowed that the networks were used as classifiers to evaluate their discrimination power. The parameters used in the training of the SOM and RSOM networks were: Random weight initialization; Initial learning rate equal to 0.8; Final learning rate equal to 0.001; Number of epochs equal to 500. Specifically for the RSOM network was used the leaking coefficient...
equal to 0.40. The results were presented in confusion matrices. In the confusion matrices each column represents the expected results, while each row corresponds to the actual results. During the simulation 80 remaining examples of the data set were used. IV. RESULTS A. Evaluation of the SOM and RSOM classifiers Table 1 shows the confusion matrices and the global accuracy of the neural networks studied. For the grid studied, the RSOM classifier obtained better performance when compared the original SOM. TABLE I. CONFUSION MATRICES AND GLOBAL ACCURACY Grid Classifiers SOM RSOM 6 x 6 7 10 5 3 62 2 63 Global Accuracy = 86.25% Global Accuracy = 91.25% B. Labeling of the neurons after the training of the SOM and RSOM networks Figure 3 shows a comparison between the labeling of the neurons after the training process, using as criteria the activation frequency. It is noticed that RSOM network had a higher organization when compared with the other network. Were used for the labels: blue in cluster 1 and red in cluster 2. Grid Classifiers SOM RSOM 6 x 6 Fig. 3. Labeling of the SOM and RSOM networks neurons. V. CONCLUSION This work aimed to evaluate the applicability of the Self-Organizing Map (SOM) and its temporal extension Recurrent Self-Organizing Map (RSOM) in the Lightning Density Patterns Recognition over the Brazilian Amazon. Its purpose was to contribute in the identification of a useful tool for the weather studies, to reduce the damages associated with this natural phenomenon. The performance analysis of the RSOM with relation to the original SOM resulted in the following main conclusions: The recurrent neural network (RSOM), used as classifier, presented improved performance over the original SOM for the time coefficient value applied; The labeling of the neurons in the maps, after the training, was better defined for the RSOM network when compared with the SOM network. It was concluded that the SOM and RSOM networks (original and temporal) confirming its usefulness as a potential tool for studies related to the Lightning Density Patterns Recognition. ACKNOWLEDGMENT The authors would like to thanks to Amazon Protection System (SIPAM) for their partnership with the Pará State University (UEPA) and to cede data and space for the realization of this and others research activities. We thank the UEPA for promote the pillars of the professional formation: teaching, research and extension. REFERENCES [1] T. Kohonen, “The self-organizing map,” Proc. IEEE vol. 78, pp. 1464- 1480, Sep. 1990. [2] T. Kohonen, Self-organizing maps. Springer Series in Information Sciences, Berlin, Germany, 2001. [3] T. Koskela et al., “Recurrent SOM with local linear models in time series prediction,” Proc. Sixth European Symposium on Artificial Neural Networks, pp. 167–172, Sep. 1998. [4] T. Koskela et al., “Time series prediction using recurrent SOM with local linear models,” International Journal of Knowledge-based and Intelligent Engineering Systems, vol. 2, pp. 60-68, 1998. [5] M. Varsta et al., “Analytical comparison of the temporal Kohonen map and the recurrent self organizing map,” Proc. ESANN’2000, pp. 273–280, 2000. [6] M. Varsta et al., “Temporal Kohonen map and the recurrent self-organizing map: Analytical and experimental comparison,” Neural Processing Letters, vol. 13, pp. 237-251, 2001.