Automatic detection of meteors using artificial neural networks

Victor Ştefan Roman[1], Cătălin Buiu

[1] **Dept. of Automatic Control and Systems Engineering, Politehnica University of Bucharest. Bucharest, Romania**
victor.roman@acse.pub.ro

Automatic meteor detection is an important activity in the field of meteor studies. In recent years, various studies have been made on this topic, underlining the interest for the automatic detection of meteors in radio or video recordings of the sky.
In this paper, three novel automatic meteor detection solutions using artificial neural networks are presented. The proposed solutions are trained to analyze radio recordings and extract the meteor samples found within. Two different types of neural networks are tested in this paper, each having its own take on how it detects meteors. Test results report high meteor detection rates on average, of above 70% for all three techniques.

1 Introduction

On its path around the Sun, Earth interacts with a large quantity of small space objects, be it dust grains or small rocks. These spatial objects, called meteoroids, hold useful information about our Solar System and therefore it is useful to study these to better understand our cosmic neighborhood. One important activity in the field of meteor studies is the actual detection of meteors. Although a part of the meteor identification is still done manually, several studies on automatic meteor detection have been made in recent times. There are several advantages with the automatic detection of meteors, ranging from ease of access to meteor data, to a more in depth understanding of meteor showers, all the way to meteor tracking and retrieval.

In the present paper, three automatic meteor detection techniques and their performances are presented. All three techniques employ artificial neural networks (ANNs) to analyze a given set of recordings, and to extract those samples of the input set that they detect as being meteors. Two types of neural networks are used in this study, the classic Multi-Layer Perceptron (MLP) network and the Self-Organizing Map (SOM). These two types of ANNs are used to analyze data coming from two types of radio recordings: raw audio data and spectrograms of the radio recordings.

2 The automatic meteor detection techniques

Detecting meteors in an automatic fashion means to be able to extract a small number of data samples from a much larger input dataset through an algorithm that is able to recognize the meteors from any other type of signals. Furthermore, the detection process has to be fast enough to be considered as a replacement for the manual detection of meteors. These requirements have led to choose neural networks as the algorithms that will tackle the automatic meteor detection problem.

ANNs are mathematical models of the biological neural networks found in the human nervous system. They emulate most of their biological counterpart's functions and structure. An ANN is a collection of interconnected neurons, which resemble the biological neurons and function in a similar manner. The ANNs need to be trained in order to solve the problem that they are used for, which means they have to be exposed to the object of their work (i.e. in the case of this study, to meteors). In light of the way they are trained, ANNs can be separated in two classes: supervised training ANNs and unsupervised training ANNs. In the present study, a network from each of the two classes was chosen to be used in the automatic detection of meteors.

Self-organizing maps

The first type of neural network trained in this study is the self-organizing map (Kohonen, 1990), (Kohonen, 2001), (Roman and Buiu, 2014). This type of ANN is a competitive learning neural network that clusters data onto a two-dimensional topographic map of neurons. The input data is clustered based on similarity, which leads to the formation of several regions within the self-organizing map where alike samples are grouped together. Depending on the problem at hand, the SOM's clustering, and the regions that are formed within the map, are an indication of the number of distinct objects that the neural network has found in the input dataset. A visual representation of a SOM network is presented in Figure 1.

The SOM is trained using an unsupervised, competitive algorithm that searches which neuron in the network is the most similar (i.e. having the smallest distance) to the input sample, and trains only that neuron and its closest neighbors, with the learning rate and neighborhood distance decaying in time. The end result of a SOM is a 2D map in which data is clustered based on similarity (i.e. similar inputs will be mapped in the same region of the output map), therefore no previous knowledge about the input samples is required, hence the unsupervised nature of the training algorithm.

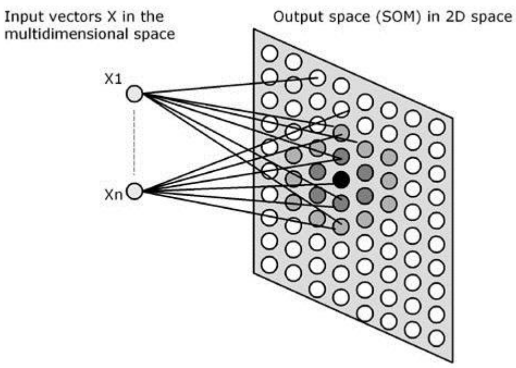

Figure 1 – Simple visual representation of a self-organizing map.

The advantages of using a SOM are the visual end result that this neural network provides, the ability to work with unlabeled data and the training algorithm that the SOM uses, which requires no previous knowledge about the training dataset.

Multi-layer Perceptrons

The second type of neural network used in this study is the MLP (Rumelhart and McClelland, 1986) network, which is one of the oldest types of neural networks. Compared to the SOM network, the MLP uses a different type of training algorithm and a different strategy of analyzing data. A MLP neural network uses supervised training algorithms, which require the network to be taught what types of data it has to be able to recognize. In figure 2 a visual representation of a typical MLP neural network is shown.

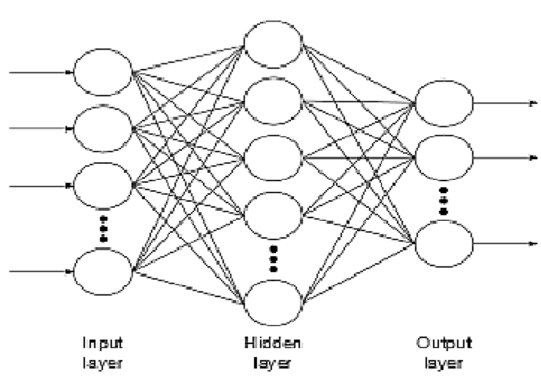

Figure 2 – Typical visual representation of a multi-layer perceptron.

The algorithm used to train the MLP networks in this study is the backpropagation algorithm. This technique implies that a sample is fed to the network and it will pass from layer to layer, going through to the output layer. The output of the network will be compared to the expected output (hence the supervised nature of the training algorithm) and the difference between the two (i.e. the error) will be propagated backwards into the network, modifying the neurons, and thus training the network to know how to respond to that type of input in the future. When the training is finished and an input is given, the MLP network will analyze the input and identify which class of signals (among those used to train the network) the input is part of.

The main advantages of using MLP networks are the speed of training and the simple and easy to read output that the network provides.

3 Results

As previously mentioned, three automatic meteor detection techniques are tested in this study. Using each of these techniques involves going through a three step process: preparing the input data for usage, training the neural network and testing the network's performances in meteor detection.

Two types of inputs were used in the present study. The first type was the raw audio recordings of radio data. These types of recordings involved two preprocessing steps before they were used to train ANNs. The first process was a filtering process, through which parts of the spectrum were eliminated from the recording (due to the fact that those parts never contained meteor samples), while the second process was a sampling process, after which the recording was broken into 0.1 second long samples, while the sampling process sliding window was 0.05 second long. These sampling process parameters were chosen because it was observed that most meteor samples are at least 0.1 second long. In Figure 3, an example of a filtered audio recording is presented.

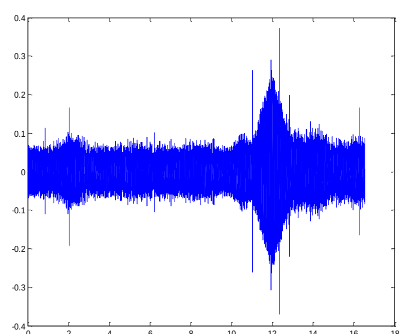

Figure 3 – Example of a filtered audio recording used for training.

The second type of inputs is the spectrograms of the radio recordings. The advantage of a spectrogram is that it offers a better visual representation of the recordings and a better way to manually detect meteors. As with the previous type of recording, the spectrograms were filtered and sampled too. The filtering took out the same uninteresting parts of the spectrum, while the spectrogram was sampled on its vertical side, due to the fact that meteor signals have a short duration, therefore they mostly appear as thin, vertical lines in the spectrogram. A spectrogram like the ones used for training is presented in Figure 4.

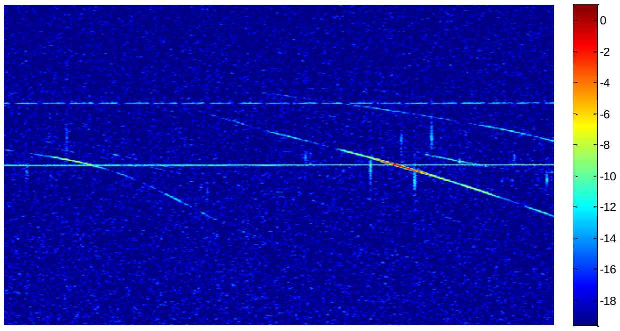

Figure 4 – Example of a spectrogram used for training.

The three proposed automatic meteor detection techniques tested in this study involved training a SOM neural network using raw audio samples, training a MLP network using the raw audio samples and training a MLP neural network using the spectrogram samples.

The first technique to be tested was the SOM trained with raw audio samples. The training dataset for this type of neural network was made of 25 audio recordings, each 5 minutes long, that were processed as mentioned above, after which they were fed to the SOMs for training. This training set contained approximately 140 meteors. The several SOMs that were trained had different sizes, containing between 50 and 200 neurons, but all had been trained for a fixed number of 1000 training epochs. The best results were obtained with an 8x16 network (Roman and Buiu, 2014), which is presented in Figure 5. The plot shown there represents the SOM's hits plot, where each hexagon is one of the network's neurons and the numbers inside represent the number of input samples mapped to each neuron.

Once the SOM was trained, a test was made to check its performance. The test dataset was built using 6 audio recordings that contain 14 meteors, which were sampled as previously described. To these inputs, another 58 samples of known meteors were added. The results of this test are presented in Table 1. These results show that the proposed solution has promising potential of automatically detecting meteors, although it is not fault free, which is obvious because of the relatively large number of false alarms (i.e. the false positive rate, which represents the number of non-meteor samples that the neural network detected as being meteors).

Table 1 – Results of the test with the proposed SOM network.

Meteor samples		Non-meteor samples	
True Positive Rate	True Negative Rate	False Positive Rate	False Negative Rate
90.28%	9.72%	10.81%	89.19%

The second technique to be tested was the MLP trained with raw audio samples. To train this network, a training set was built with 230 meteor samples and 200 non-meteor samples. The MLPs trained were built with quite similar architectures, the only difference being the number of neurons in each MLP's hidden layer. Thus, the MLP networks were built with 551 neurons in the input layer and 2 neurons in the output layer, while the number of neurons in the hidden layers varied between 50 and 200.

The dataset used to test this technique was built with 161 meteor samples and 11536 non-meteor samples. This dataset was fed to the different MLPs, with the performances of the neural networks being presented in Table 2. These results show that the proposed solution has the ability to recognize meteors from a given dataset, but similar to the SOM case, it falsely deemed a good number of non-meteor samples as being meteors. Similar to the SOM solution, even though the percentage of false alarms was not large compared to the percentage of positive non-meteor detection, the number of non-meteor samples falsely detected as being meteors was larger than the number of meteors correctly detected.

Table 2 – Results of testing the MLPs trained with audio samples

Meteor samples		Non-meteor samples	
True Positive Rate	True Negative Rate	False Positive Rate	False Negative Rate
86-93%	7-14%	10-24%	76-90%

The third technique proposed in this study involves the training of MLP neural networks using spectrogram samples. To test this technique, a new training set was built which contained 600 meteor samples and 500 non-meteor samples. As with the previous proposed technique, various MLP networks were trained using this training dataset. The neural networks were built with 595 neurons in the input layer, 2 neurons in the output layer and a varying number of neurons in the single hidden layer.

Table 3 – Results of testing the MLPs trained with spectrogram samples

Meteor samples		Non-meteor samples	
True Positive Rate	True Negative Rate	False Positive Rate	False Negative Rate
70-77%	23-30%	46-60%	40-54%

For this technique, the test dataset was built with 245 meteor samples and 200 non-meteor samples. Depending on the size of the trained MLPs, the results obtained after testing are presented in Table 3. Compared to the previous two techniques, this one shows lower performances, especially in regards to the false positive rate (i.e. the number of non-meteor samples that are deemed as being meteors by the neural network).

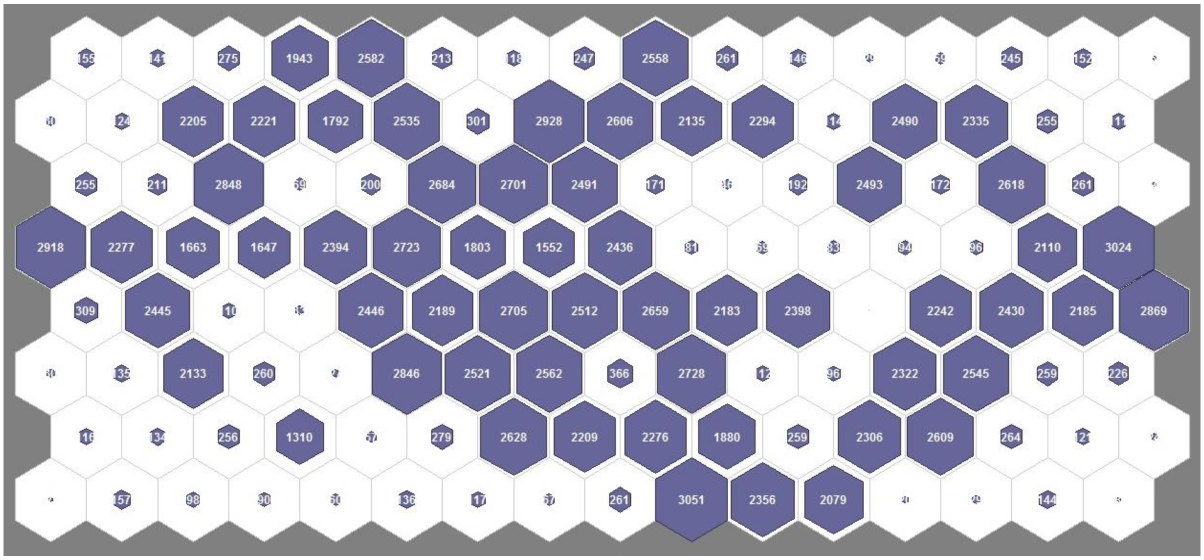

Figure 5 – The resulting self-organizing map.

4 Conclusions and future work

The three techniques presented within this study all show promise in the field of automatic meteor detection. All of them offer high detection rates, which allows for the extraction of the majority of meteors from a given test dataset. The only problem, recurring with all three proposed techniques, is with the quite high (in actual number of samples, not in the overall percentage) false positive rate, especially in the case of the MLPs trained with spectrogram samples. The size of the problem is more obvious when we compare the numbers behind the true positive and false positive rates. As for the reasons behind these high false positive rates, there are several possibilities: the size of the sampling window, size of the window’s slide, or the similarity between meteor signals and non-meteor artifacts (e.g. planes).

However, despite the problems with the false positive rates, the three proposed techniques are decent solutions to the problem of automatic detection of meteors. Each technique has its own advantages that make it a good candidate. The SOM networks offer an easy to interpret, visual output. This has the great advantage of being able to work with unknown or unlabeled data because the SOM network gives verdicts based on the similarity of data and not on previous knowledge about it. The MLPs are easier to train than a SOM and offer a very precise output. Furthermore, their supervised training algorithm insures that the neural networks know what a meteor looks like. Above all, a general attribute that all the techniques have is the high speed of making a decision, each neural network requiring only a brief moment to check a given input and deciding whether it is a meteor or not.

As for future work, the main focus will be on improving detection rates and lowering the false positive rate, thus allowing the three proposed techniques to detect more real meteors and to eliminate fake warnings. To tackle these issues, changes will have to be made in several areas such as: the sampling of the data (changing the sampling window size or slide), size of the neural networks, length of their training or depth of the networks (in the case of MLPs).

Acknowledgments

This work was supported by a grant from the Romanian National Authority for Scientific Research, CNDI-UEFISCDI, project number 205/2012 and by a grant from POSDRU, project number 137390.

V.S. Roman performed part of this work in a research stage at Institut d’Aéronomie Spatiale de Belgique and would like to thank Hervé Lamy for his kind support.

References

Kohonen T. (1990). “The self-organizing map.” In *Proc. IEEE*, September 1990, **78**, no. 9, pages 1464–1480.

Kohonen T. (2001). Self-organizing maps. Third Edition. Berlin: Springer Verlag.

Roman V. S. and Buiu C. (2014). “A self-organizing map based solution to the automatic detection of meteor echoes in radio recordings”. In *Proceedings of the 6th Edition of the International Conference on Electronics, Computers and Artificial Intelligence*, Bucharest, 23–25 October 2014. Accepted.

Rumelhart D. and McClelland J. (1986). Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Volume 1: Foundations. MIT Press.