AUTOMATIC DETECTION OF METEORS USING ARTIFICIAL NEURAL NETWORKS

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Introduction

This project presents three techniques based on artificial neural networks (ANNs) that aim to automatically detect meteors from a given dataset.

In this poster, the two types of ANNs will be presented, along with the results of the tests made for the proposed techniques.

Automatic meteor detection techniques

The proposed solutions use two types of input data to train and test the artificial neural networks.

- ➢Raw audio recordings (see Figure 1)
  - •Filtered to eliminate uninteresting spectrum
  - •Sampled with 0.1 seconds window and 0.05 seconds window slide
- ➢Spectrograms of radio recordings (see Figure 2)
  - •Filtered to eliminate uninteresting parts of the spectrum
  - •Sampled vertically, to take advantage of meteor shapes

Self-organizing map (SOM) trained with raw audio samples

- ➢SOM = competitive, unsupervised ANN
- ➢The SOM clusters the input data onto a 2D topographic map of neurons (see Figure 3)
- ➢Data in SOM is clustered based on similarity
- ➢The SOM's output map has a size of 8x16 neurons

Multi-layer Perceptron (MLP) trained with raw audio samples

- ➢MLP = supervised ANN with Backprpagation training
- ➢An MLP is a neural net that has neurons organized in layers, with each neuron in one layer being fully connected to the neurons in the next layer. The information passes through the network from layer to layer
- ➢An MLP network is trained with samples that the user has knowledge of (i.e. the input samples are labeled before being fed to the MLP)
- ➢This MLP's architecture is: 551 neurons in the input layer, a number of neurons in the hidden layer and 2 neurons in the output layer

Multi-layer Perceptron (MLP) trained with spectrogram samples

- ➢This MLP is trained with meteor and non-meteor samples extracted from the spectrograms
- ➢The MLP's architecture is: 595 neurons in the input layer, a number of neurons in the hidden layer and 2 neurons in the output layers

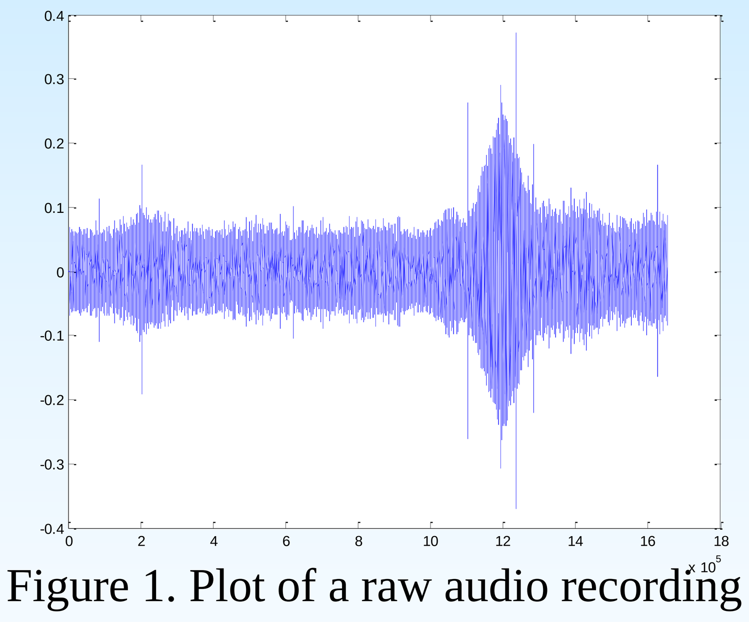

Figure 1. Plot of a raw audio recording

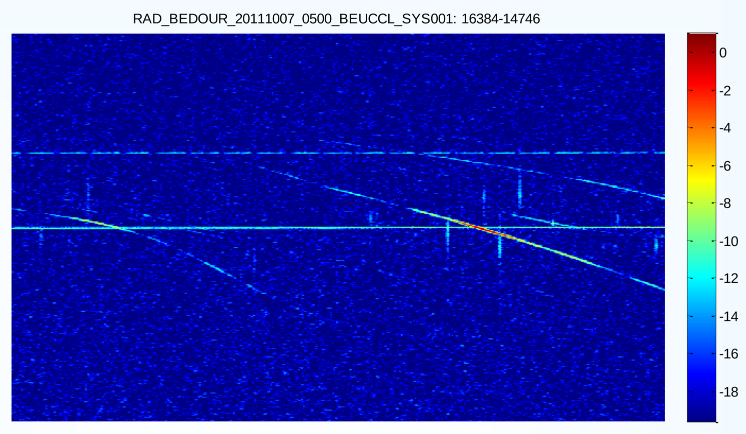

Figure 2. Spectrogram of a radio recording

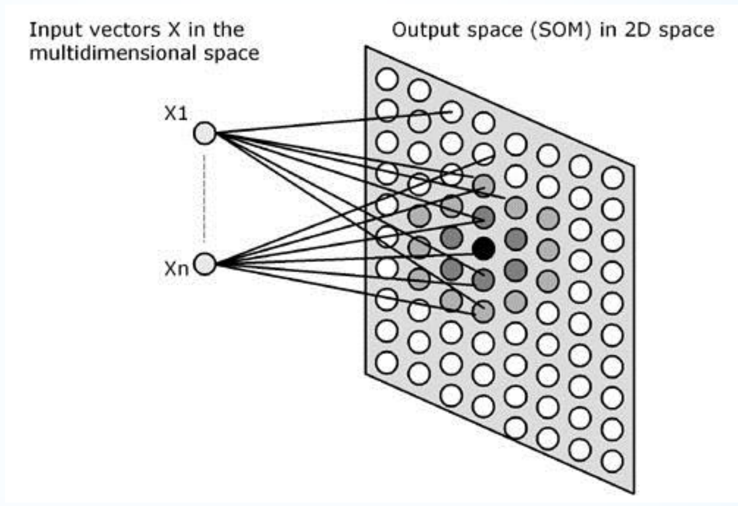

Figure 3. Typical SOM representation

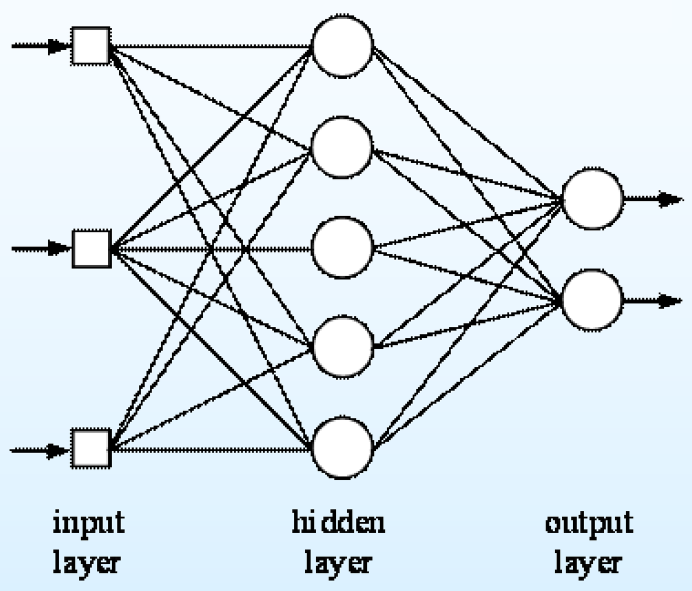

Figure 4. Typical MLP representation

Results

SOM trained with raw audio samples

- ➢8x16 map trained with samples from 25 recordings for 1000 epochs; the training result is presented in Figure 5
- ➢The SOM was tested with a dataset comprising 72 meteor samples and 35976 non-meteor samples
- ➢The results of the test are presented in Table 1

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%

Table 1. SOM with audio samples test results

Results (continued)

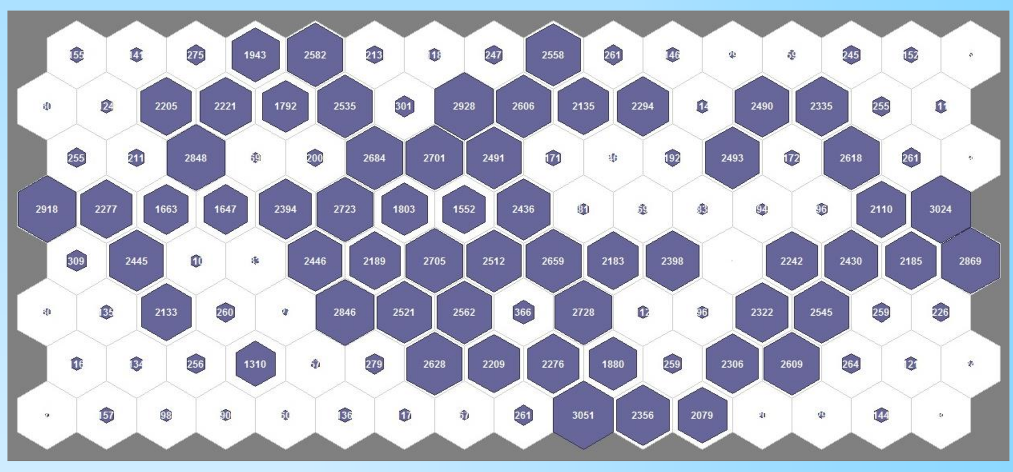

Figure 5. The SOM obtained through training

MLP trained with raw audio samples

- ➢The neural networks were built with between 50 and 200 neurons in the hidden layer
- ➢Each MLP was trained with a dataset of 230 meteor samples and 200 non-meteor samples
- ➢The networks were tested with a dataset containing 161 meteor samples and 11536 non-meteor samples. The results are shown in Table 2

Meteor samples		Non-meteors samples	
True positive rate	True negative rate	False positive rate	False negative rate
86-93%	7-14%	10-24%	76-90%

Table 2. MLP with audio samples test results

MLP trained with spectrogram samples

- ➢Each MLP network was built with between 50 and 200 neurons in the hidden layer
- ➢The MLPs were trained with a dataset of 600 meteor samples and 500 non-meteor samples
- ➢The neural nets were tested with a dataset of 245 meteor samples and 200 non-meteor samples. Results are shown in Table 3

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%

Table 3. MLP with spectrogram samples test results

Conclusions and Future Work

Proposed techniques show promising results. All three of them provide high meteor detection rates. Combining this with the high speed of decision that the ANNs have makes the proposed techniques to be good solutions for automatically detecting meteors.

The main drawback of the proposed techniques is the quite high false positive rates, and especially the fact that number of falsely detected non-meteor samples is greater than the number of correctly detected meteor samples.

Future work with these techniques involves finding optimal solutions that will keep (or enhance) the current true positive detection rates, but will reduce the false detection rates.

Acknowledgements

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