Automatic detection of meteors in the BRAMS data

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BRAMS is a Belgian network consisting of one beacon and 26 receiving stations to detect radio meteors by forward scattering. Because of the large amount of data generated by these stations, a good automatic detection algorithm is needed. In this paper, four algorithms currently under test are briefly described. Application of three of them to an example of BRAMS data is shown with a comparison to manual count in order to emphasize the advantages and disadvantages of each method.

1 Introduction

The BRAMS (Belgian RAdio Meteor Stations) network consists of one beacon located in Dourbes and 26 receiving stations spread over Belgium. Each station records continuously a bandwidth of 2.5 kHz more or less centered on 49.97 MHz, the beacon frequency. The data are stored in WAV (sound) files of 5 minutes each. In total about 7500 files (288 files per station) are generated per day. Checking all those files manually for meteors is too much time consuming, so an automatic detection algorithm is mandatory. In this article, a quick overview of four different automatic detection methods of radio meteors in BRAMS data files is provided. Each method works either on the raw data obtained in the time domain or on a spectrogram.

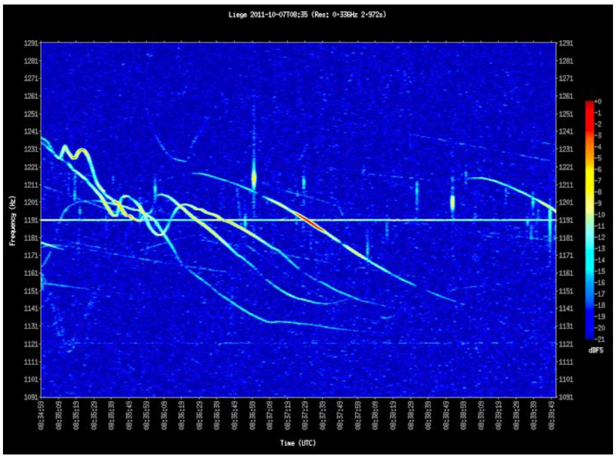

Figure 1 – A typical spectrogram from a BRAMS receiving station. Frequency range is 200 Hz centered on the beacon frequency. Duration is 5 minutes. Power is color coded. The horizontal line in the middle of the spectrogram is the direct reception of the BRAMS beacon, the inverse S-shaped lines are reflections on airplanes moving on a straight line and the short vertical lines are meteor echoes. The complex shapes on the left hand side of the spectrogram are also produced by airplanes which change directions. Manual count gives 17 underdense meteors.

A spectrogram is a visual representation of the spectrum of frequencies in a signal as it varies with time. It is obtained from the time signal using a FFT (Fast Fourier Transformation). The result is a two-dimensional representation of the signal, where the horizontal axis represents time, the vertical axis is frequency and the color indicates the power of the signal. *Figure 1* shows a typical BRAMS spectrogram.

Three of the four methods are currently under evaluation by the BRAMS team by comparing their results to manual counts. An example is provided below for each method. So far the comparison is made only for short-lived underdense meteor echoes with a typical duration of a few tenths of seconds at most. These meteor echoes constitute the majority of meteor echoes detected in BRAMS data.

2 Image recognition on spectrograms (I)

The first method, developed by Pierre Ernotte, uses image recognition on spectrograms. The first step in the algorithm is the binarization of the spectrogram. Only pixels above a certain threshold are kept to filter out noise and their values are set to 1. It means that the information about the variations in the signal power is lost. Then the algorithm applies a vertical erosion (Gonzalez and Woods, 2007) using the fact that underdense meteor echoes appear mostly vertical in spectrograms while the beacon frequency and the plane echoes have a dominant horizontal component. The erosion operator superimposes a mask to each pixel with a value of 1 and keeps its value if all pixels underneath the mask are equal to 1, otherwise it is set to 0. In our case the mask is a vertical line whose length is chosen to be larger than the typical frequency width of plane echoes or of the beacon frequency. This vertical erosion may divide some meteor echoes in different parts. Dilation (Gonzalez and Woods, 2007) along columns and adjacent lines is then performed to reconnect them.

Since this technique is performed on spectrograms, it is easy to compare the results with manual counts which are also made on spectrograms (Calders et al., 2014). Planes are removed decently well, and the method provides good results for short meteors which appear mostly vertical (see *Figure 2*). However, some faint meteor echoes can be missed, when their vertical/frequency signature is discontinuous and hence they may not survive the erosion. The method does not work for long lasting meteors (not present in the example in *Figure 1*) which have a large horizontal component and/or a complex structure. Also the creation of the spectrogram as well as the erosion/dilation are very time consuming operations. Finally the method contains several empirical parameters which may have to be adapted for different BRAMS stations.

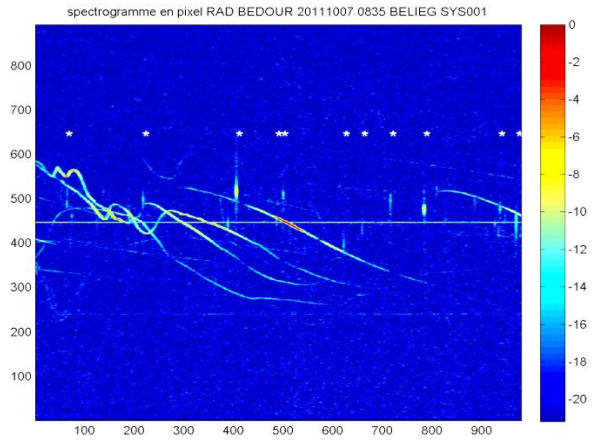

Figure 2 – Application of Ernotte's method to the example spectrogram of *Figure 1*. Units for the axes are here given in pixels. The method detects 11 meteors (white dots) but six faint meteors do not survive the erosion and are missed.

3 Image recognition on spectrograms (II)

Another method using spectrograms has been developed by Emil Kraaikamp. First, an horizontal median filter is applied to the spectrogram to remove the direct reception of the beacon signal (and possibly other local transmitters). Then a set of oblique median filters is used to remove the airplane echoes, because those signals can be approximated by a set of straight lines with different inclinations and lengths. Finally a detection threshold using the median and the MAD (median absolute deviation) is used to distinguish between meteors and noise.

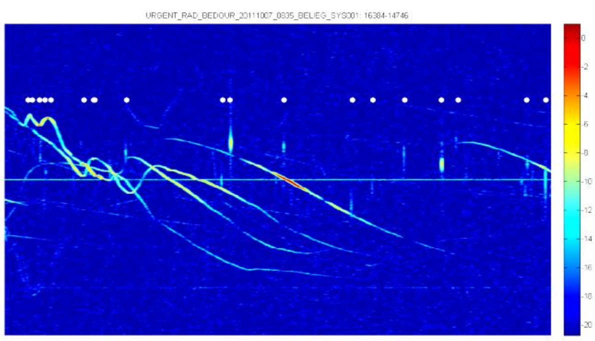

Figure 3 – Application of Kraaikamp's method to the same example in *Figure 1*. The method detects 18 meteors. Some parts of the complex airplane echoes (on the left side of the picture) are not fully removed and incorrectly detected as meteors (3 cases). 1 faint meteor is not detected.

Like for Ernotte's method, comparison with manual counts is easy. The method does not use binarization, which gives the possibility to use the signal power in the final detection step. It removes quite well the plane echoes as long as the shape is simple (i.e inverse S-shaped lines). But it can produce false meteor detections when complex airplane echoes are present in the spectrogram (see *Figure 3*). Another drawback is again that the method is CPU intensive.

4 Meteor detection using only the time signal

Tom Roelandts is developing a method based only on the signal in the time domain. First, an adequate filtering is applied to keep only frequencies within 200 Hz below or above the beacon frequency (where all meteor echoes appear). This strongly reduces the noise in the data. Then the method computes running averages on a short and a long timescale (typical of the duration of an underdense meteor resp. plane echo) and divides them to obtain an indicator signal. The basic idea is that an underdense meteor echo will contribute strongly to the short running average but not to the long one, hence creating a peak in the indicator signal. An appropriate threshold is used to detect these peaks. More information about this method can be found in Roelandts (2014). Here we only provide in *Figure 4* the results of the application of this method to the raw data used to compute the spectrogram in *Figure 1*. The method may miss faint meteor echoes appearing at the same time as the brightest part of an airplane echo. In this case the resulting peak of the indicator signal can be lower than the threshold and the meteor is missed.

Since this method does not compute spectrograms, its main advantage is that it is much faster than the previous ones. Also the duration of a meteor can be measured more accurately in the time domain than in a spectrogram. It also has only three parameters. The choice of the threshold is however currently empirical and varies from station to station.

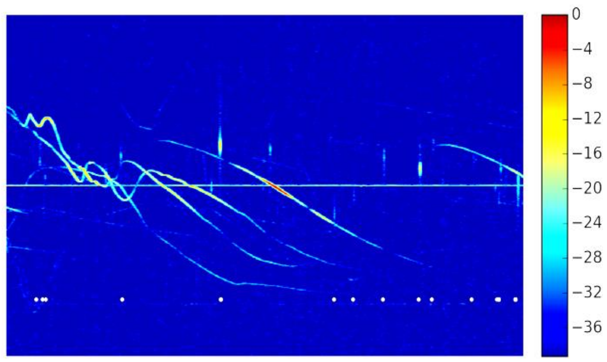

Figure 4 – Application of Roelandts 'method to the raw data used to compute the spectrogram in *Figure 1*. The method detects 14 meteors whose locations have been added to the spectrogram a posteriori for comparison with the previous methods. Three meteors are missed as they appear at the same time as the brightest (red) part of airplane echoes (see text).

5 Meteor detection using neural networks

This method is developed by Victor Roman and is based on two different types of artificial neural networks. Firstly, the Self-Organizing Map, SOM, (Kohonen, 1998) is a type of neural network that produces a low-dimension (typically two) representation (map) of the input signals (in our case e.g. a vector containing the power or amplitude recorded in WAV files). A SOM consists of components called neurons whose spatial location in the map corresponds to a particular domain of the input signal patterns. SOM operates in two successive modes: training builds the map using input examples while the mapping automatically classifies a new input vector. The idea behind using this method is that meteor echoes will be mapped on specific meteor neurons, while plane echoes or noise will be mapped to different locations of the map. The SOM is trained using unsupervised learning (meaning, in our case, that the user does not tell the network that a meteor is given as input).

Another type of artificial neural network considered is the Multi-Layer Perceptron, MLP (Gardner and Dorling, 1998) which consists of multiple layers of interconnected neurons, representing a non-linear mapping from an input vector to an output vector. Each neuron in a given layer is connected to all neurons from the previous and subsequent layers with weights that are calculated using a non-linear transfer/activation function. For this study, a feed forward architecture was chosen, meaning that the data is only propagated from the input to the output layer. Training such a neural network requires a supervised algorithm, the one used here being the back propagation algorithm. In both methods input data can be taken either from the (filtered) raw data (e.g. a vector with power samples taken during 0.1 sec) or from spectrograms (e.g. a vector with pixel intensities taken as one of the spectrogram's vertical lines).

More information about these methods and preliminary results can be found in (Roman, 2014). The results are not discussed here as they cannot easily be compared to the other methods.

6 Conclusion and further work

We have briefly presented four different algorithms considered for the automatic detection of radio meteors in the BRAMS data. Two of the methods are based on image recognition on spectrograms, one uses neural networks and one detects the meteors using only the time signal.

These methods have been applied to one test case for comparison only and to illustrate the strengths/weaknesses of each method. No firm conclusion can be reached from this test case only. Statistical studies on a large set of data are necessary and currently carried out by the BRAMS team. All methods work relatively fine for short-lived (underdense) meteors except when many plane echoes with complicated shapes are superimposed on them (e.g. in the left part of *Figure 1*). The longer (overdense) meteor echoes (not present in *Figure 1*) pose another real challenge. Their automatic detection will be considered in a later phase of the project.

Results from the various automatic detection methods must be assessed by comparing with manual counts. At the moment there is only a single day of manually detected meteors for one receiving station. We plan to extend our manual count dataset to more stations, several days, with and without high meteor stream activity, in order to better assess the different automatic detection algorithms.

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