Classification and Characterization of "Ugly" Specular Radar Meteors using Machine Learning

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ABSTRACT

Specular meteors, characterized by their reflective properties, offer valuable insights into atmospheric composition, dynamics, and meteor properties. Traditional methods of classifying meteors rely on manual analysis or mathematical signal processing techniques. We have identified two problems with this approach. Firstly, these methods exclude all except a very small selection of "perfect" underdense and high-SNR meteor trails. These "perfect" meteor trails are useful for determining atmospheric winds, meteor radiant distributions, velocities, and more, but there may be additional valuable insights about the atmosphere that are overlooked by rejecting many of the observed meteors. Secondly, the signal processing techniques must be designed for specific radar systems operating with their own settings, such as power, frequency, PRF, and more. Thus, the data processing techniques must be modified to analyze meteor detections from different systems, costing time and energy. By leveraging advancements in machine learning, this study aims to develop an automated classification framework for specular meteors detected by all-sky radars, with the goal of extracting new information about the atmosphere and meteor properties from these detections, as well as offering a fast and effective method of signal processing that is applicable to specular meteor radar data regardless of the system used to make the observations.

INTRODUCTION

- The objective is to develop software that can be distributed to Specular Meteor Radars (SMR) all over the world that will collect data on the "ugly" trails, as these have never been analyzed before.
- The software will focus mostly on machine learning techniques that are not sensitive to hardware signatures, such as radar pulse width, PRF, power, etc.
- It will have to be fast enough to process data in real time, as storing raw SMR data is impractical due to its size and the remote nature of many of the stations.
- This study presents a first step towards characterizing the "ugly" meteors by using unsupervised learning techniques to differentiate and extract meteor types, to ultimately form a training database for supervised learning algorithms.
- Hierarchical clustering is employed based on mathematically defined signal features.

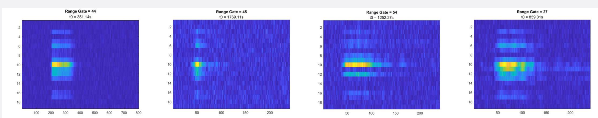


Figure 1: The RTI plots of some meteors. The "wings" seen in adjacent range bins are due to decoding the Barker code used during transmission.

METEOR EXTRACTION

- Signals of interest are identified by a simple adaptive thresholding method and a window is created around the candidate.
- The rise time, duration, SNR, and other features are used to quickly identify likely meteors.
- The meteor trace is analyzed using existing methods to extract some characteristics such as height, velocity, and position.
- Typically, meteor traces that do not adhere to a strict set of criteria are ignored. The selected meteors are effective for measuring winds, for example.
- These criteria commonly used to reject meteor candidates are forsaken for our purposes – we want the bad ones too!

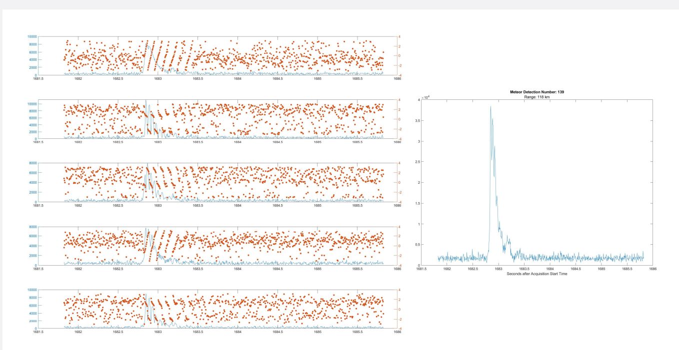


Figure 2: On the left, the received signal magnitude and phase for each receiver in the 5-receiver array. The magnitudes are combined to form the plot on the right.

HIERARCHICAL CLUSTERING

- This method was selected due to its flexibility and the ability to perform this type of clustering without specifying a number of clusters. This was important because the number of potential signal types was unknown, given that there is no existing record of these types of meteors. Hierarchical clustering creates a type of hierarchical tree called a dendrogram, which can be "cut" at any point to create as many or as few clusters as is deemed best.
- Features are defined for each meteor trace based on its shape and other characteristics. These features include its 3rd degree polynomial fit, spectral bandwidth, kurtosis and skewness, and energy.
- Hierarchical clustering was applied to the matrix containing the features of each signal.
- The clusters were analyzed and the dendrogram was "cut" selectively based on observation of the resulting groups.
- The categories presented below represent a good basis for meteor type definitions.
- Features can be tuned by implementing more advanced techniques to tailor the resulting clusters. This might include higher order polynomial fitting, changing the importance of frequency to the similarity score, etc.

THE SKiYMET ALL-SKY METEOR RADAR

- The data used for this study was from a SKiYMET system installed at Culebra, Puerto Rico.
- This SMR is made up of one transmitter and five receivers, located near one another.
- The receivers are crossed dipoles, and the five of them form a larger cross with inter-receiver spacing of 2 and 2.5 wavelengths. This allows for low ambiguity when identifying the direction of the received signal while also reducing the interference between antennas.
- Due to the co-location of the transmitter and receiver, the radar can only detect meteors whose trajectories are perpendicular to the radar's line-of-sight to the meteor.

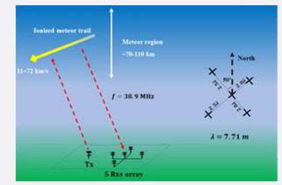
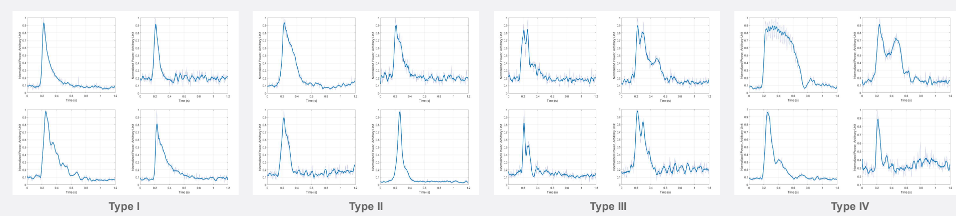


Figure 3: An example of the geometry of the SkiYMET system. The one used for this study was configured slightly differently. This image is courtesy of Yi et al. of USTC

CLUSTERING RESULTS

- Clustering shows successful preliminary results. Types I, II, and III were selected from the dendrogram to demonstrate the ability of the algorithm to identify and differentiate different meteor "styles".
- Type I are good, underdense echoes that demonstrate exponential decay.
- Type II display some deviation from the strictly exponential decay trend. They appear to have two decay rates.
- Type III exhibit two noticeable power spikes. This may be an artifact of Fresnel scattering, noise, or something else.
- Type IV represents a combination of some of the outliers identified by the hierarchical clustering algorithm.



CONCLUSIONS

The study has produced strong results that demonstrate the software's ability to extract and categorize various meteor types from raw data without relying on hardware-specific analysis techniques. Hierarchical clustering proved to be an apt method for identifying meteor types and can be improved by tuning the feature extraction. Work remains to be done to create a full training set for meteor extraction networks, but a strong baseline has been demonstrated.

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