### WHISTLER WAVES DETECTION USING MACHINE LEARNING

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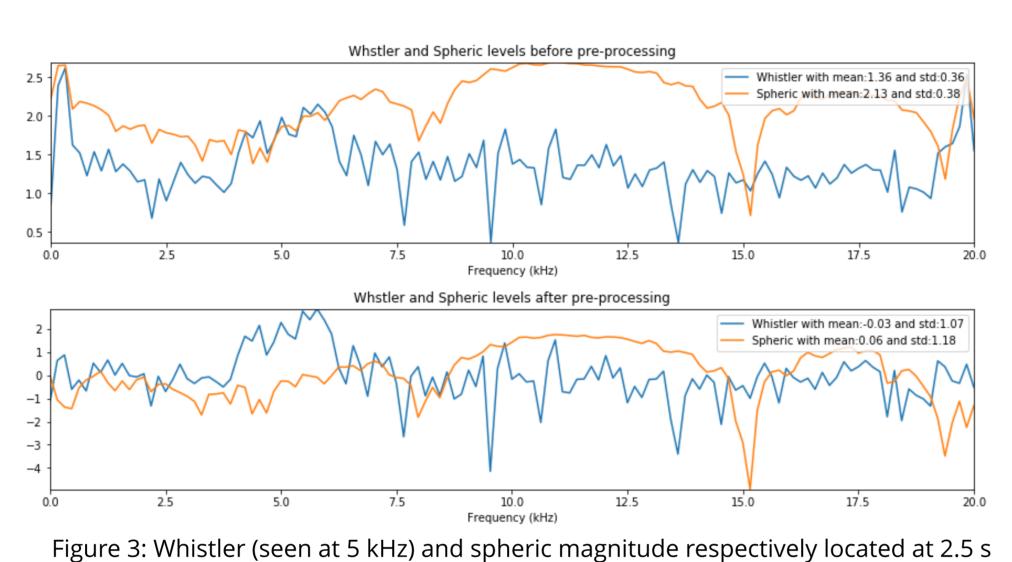




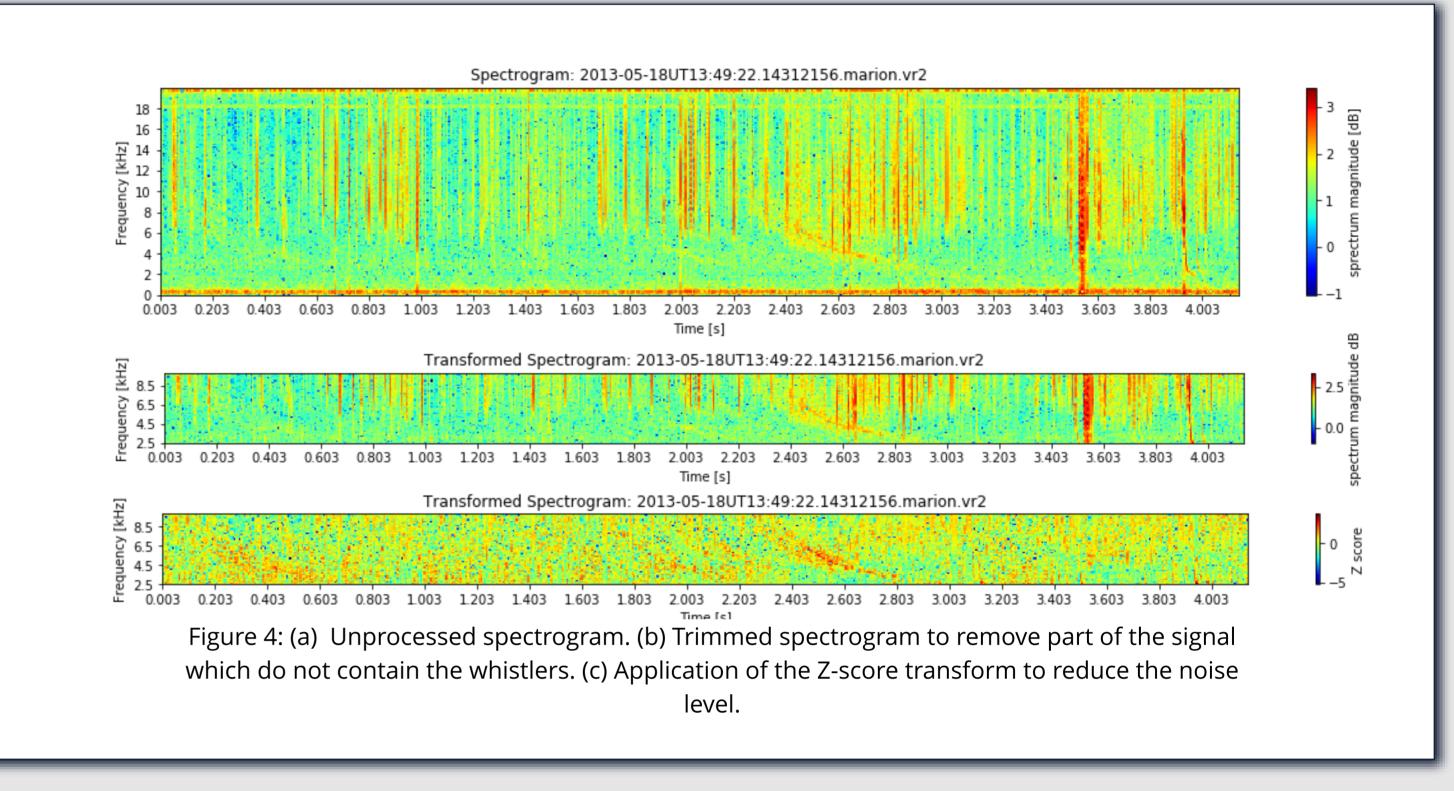
# **BACKGROUND** Figure 1: Whistler waves traveling through the Earth's ionosphere [1]. The propagation time delay of these waves is dependent on the plasma density along the propagation path. This enables the use of whistler wave observations for characterising the plasmasphere in terms of particle number and energy density.

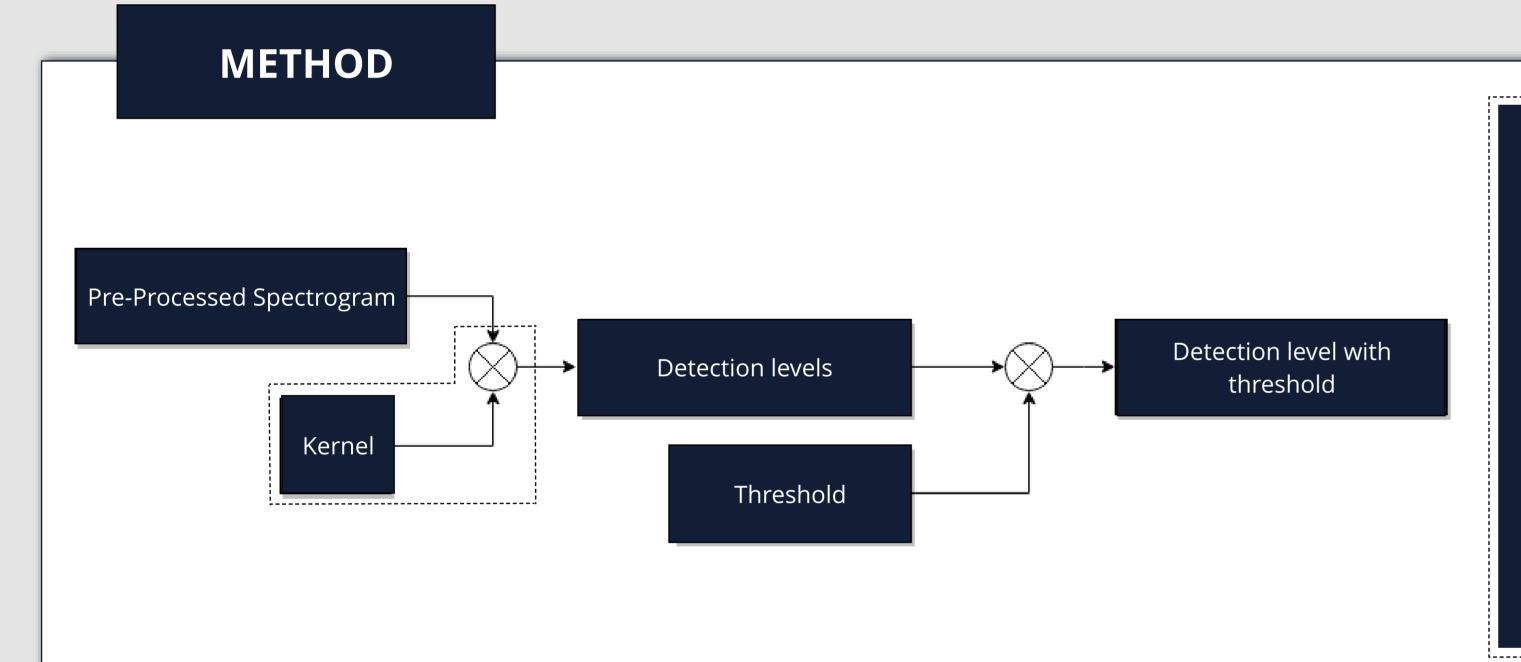
#### DATA ADC signal: 2013-05-18UT13:49:22.14312156.marion.vr2 The data provided for the research is collected and labeled using the Automatic Whistler Detector (AWD) designed by Janos L. et. al. [2]. Spectrogram: 2013-05-18UT13:49:22.14312156.marion.vr2 Each sample has a length of 4 to 12 seconds depending of the number of Ineucy [kHz] 12 10 8 whistler detected and the time interval between them. For this research, **2195 labeled** samples collected at Marion island in 2013 are used. The samples are Figure 2: (a) Raw data collected by a Automatic Whistler Detector (AWD) [2] node at partitioned into **1471 training** Marion island showing strong presence of spherics of magnitude above 20000. (b) samples and 725 testing samples. Time-frequency representation of the data showing the 5 kHz positions of the whistlers at 0.3, 2, 2.2, and 2.6 s.

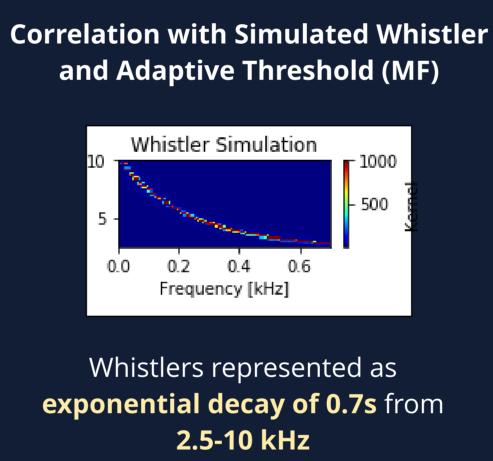
## PRE-PROCESSING **Z-score Transform** $X_z = Z\{X\} = (X-\mu)/\sigma$ $\mu_{Xz} = 0$ , $\sigma_{Xz} = 1$ Apply on each axis: $z_{ij} = Z_i \{ Z_j \{ x_{ij} \} \}$ and 2 s. (a) Whistler is -0.5 dB below the spheric (b) After pre-processing, the whistler is



+1.5 dB above the spheric.



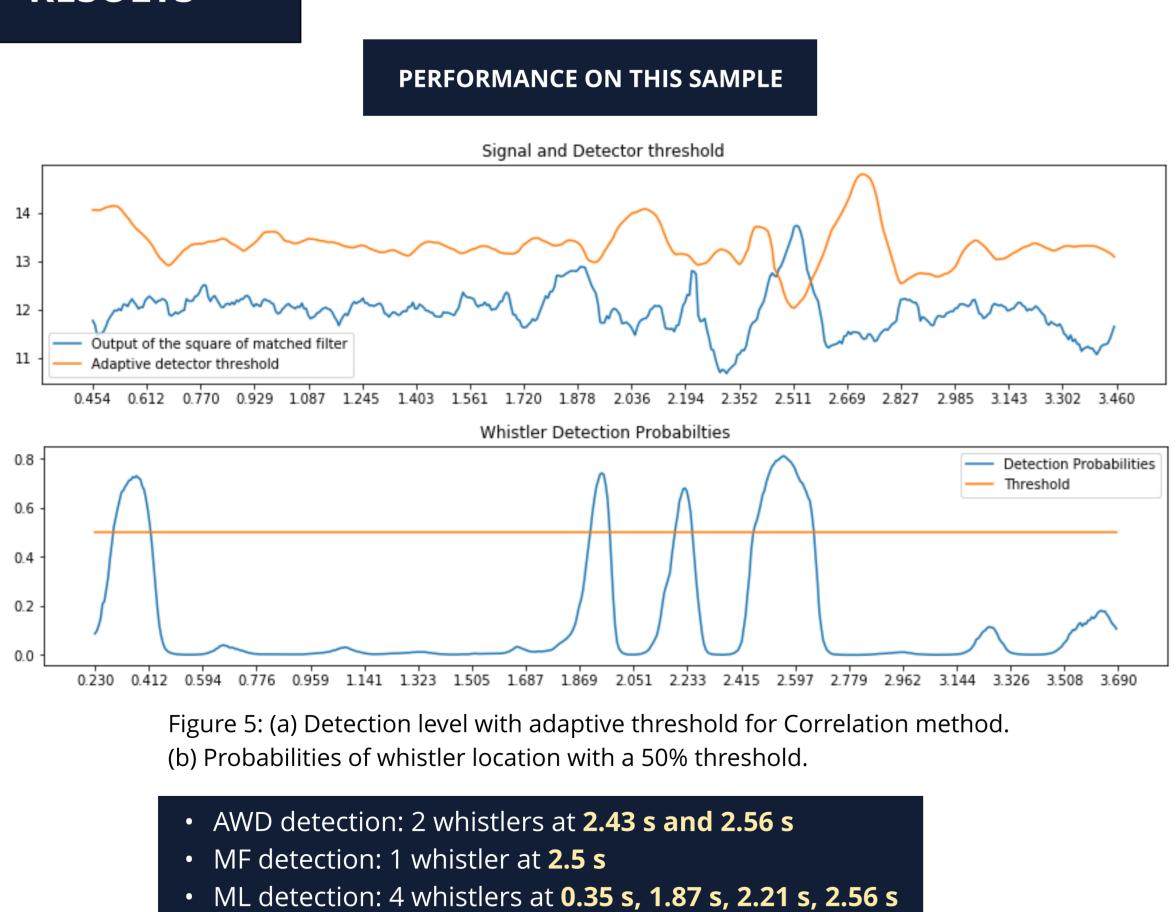




Detection using a Convolutional Neural Network (ML) We use the output provided by AWD to create **cuts of 0.7 s** from 2.5-10 kHz range. We train a CNN with a total of **13417** samples (using data augmentation) with 20% for **cross-validation**. The CNN is made of **4 2-D convolutional** layers, a Max pooling layer, 3 Dense layers and few Dropout layers. The classifier obtained has a **accuracy of 95%** and a **loss of 0.1** after the

25th epoch.

### **RESULTS**



### **OVERAL PERFORMANCE**

Table 1: Overall performance of the matched filtering (MF) method and the machine learning (ML) method on the data.

	TRAINING DATA		TEST DATA	
	MF	ML	MF	ML
PRECISION	79.9%	69.7%	80.7%	70.5%
RECALL	72.9%	82.5%	71.5%	81.2%
F1-SCORE	76.2%	75.6%	75.8%	75.5%
FALSE ALARM RATE	20.1%	30.3%	19.3%	29.5%
MISDETECTION	27.1%	17.5%	28.5%	18.8%

- AWD has a misdetection rate of 10% and a false alarm rate of 20-50% [2]. Since AWD is used as the ground truth, its error propagates through metric of evaluation of the matched filtering method and the machine learning model.
- MF detection has a misdetection rate of 28.5% and a false alarm rate of 20.1%.
- ML detection has a misdetection rate of 18.8% and a false alarm rate of 29.5%. The false alarm are questionable since the AWD missed some events.

### **CONCLUSION & CHALLENGES**

- The data available for the research is limited. Only 2195 samples, that is 3 hours of collected data are used to create the model above.
- The ground truth is not available to us, as a result, the labels provided by the AWD algorithm is used as a ground truth.
- The Matched Filtering approach using an adaptive threshold has many tweaking parameters and finding an optimal set is difficult.
- The Machine learning model perform well in practice and can detect whistler difficult to see with the human eye and not detected by the AWD algorithm.

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**REFERENCES**