Geomagnetic Data and Artificial Neural Networks

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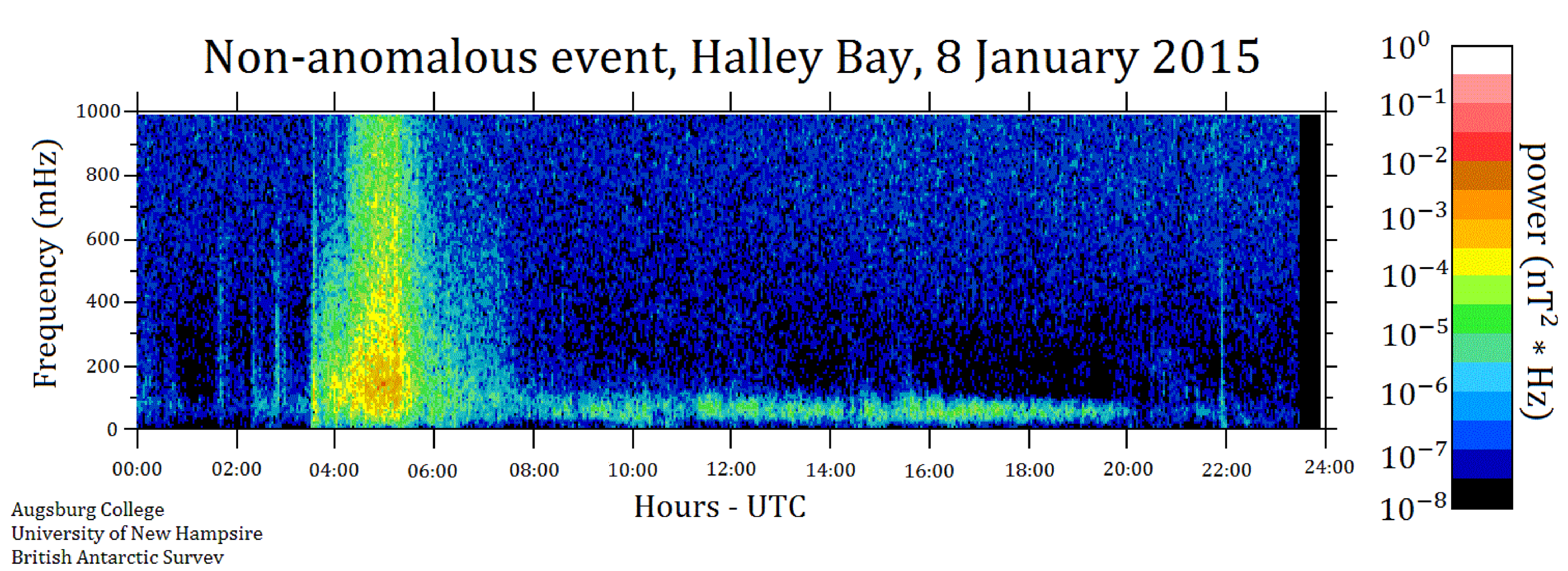
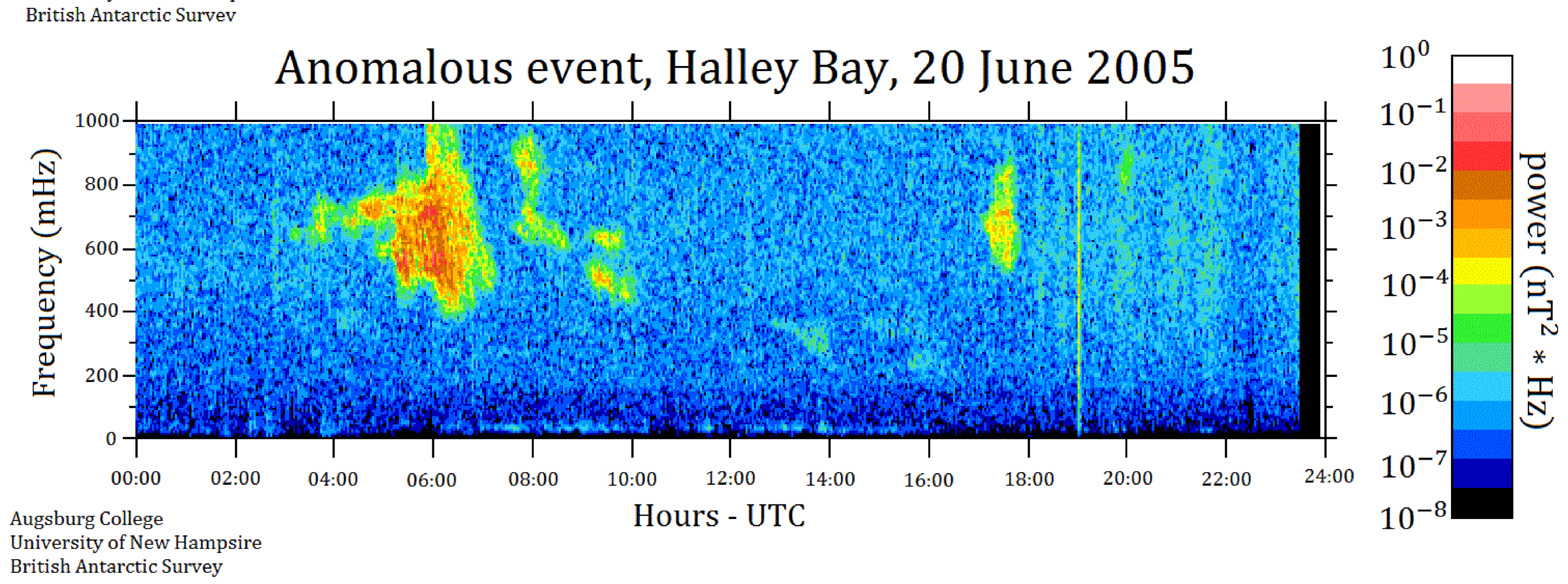
Abstract

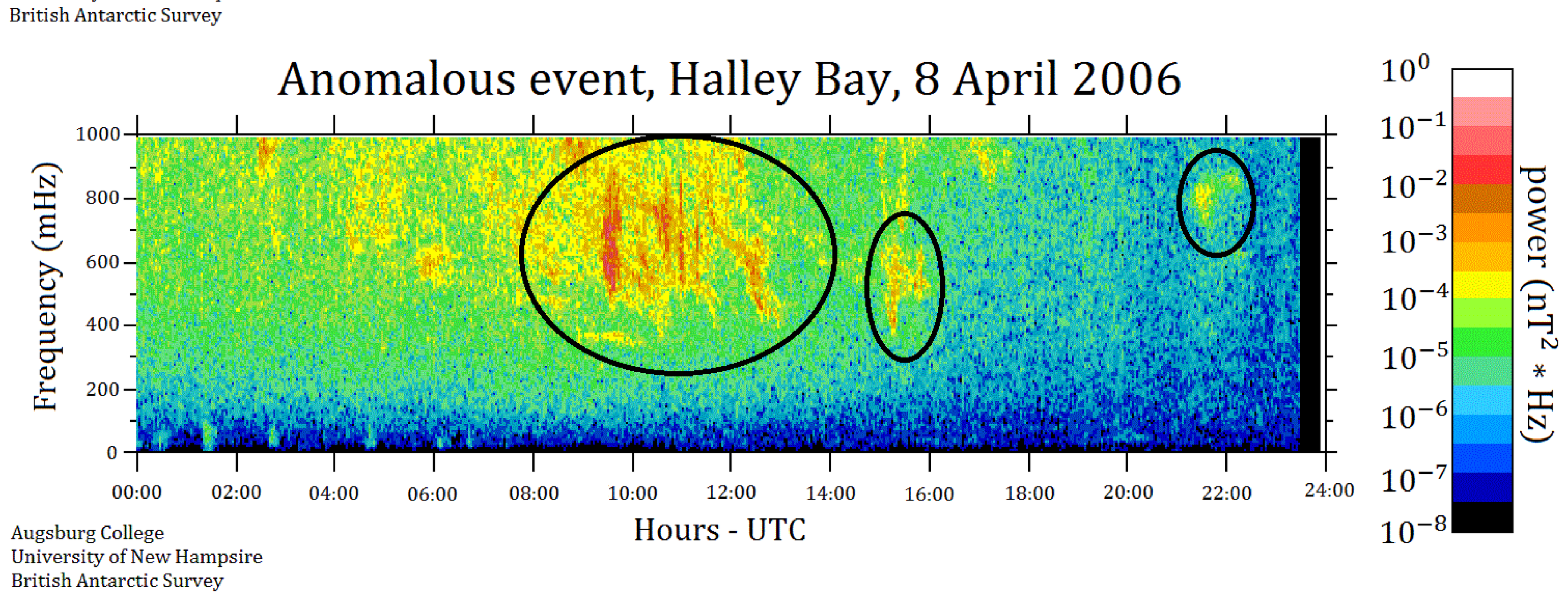
The purpose of our research was to automate the recognition of anomalies in geomagnetic data from the MACCS project. This automation was to be a study in the application of artificial neural networks. There was not enough MACCS project data to train an artificial neural network, and so geomagnetic data from the British Antarctic Survey was used instead.

Objective

Utilize the python machine learning library called Keras to experiment with different convolutional neural network architectures for the purposes of identifying anomalies in BAS data.







Results

Our research demonstrated that the type of activity referred to as anomalous by the MACCS project could be identified in BAS data by an artificial neural network with up to 96.58% accuracy.

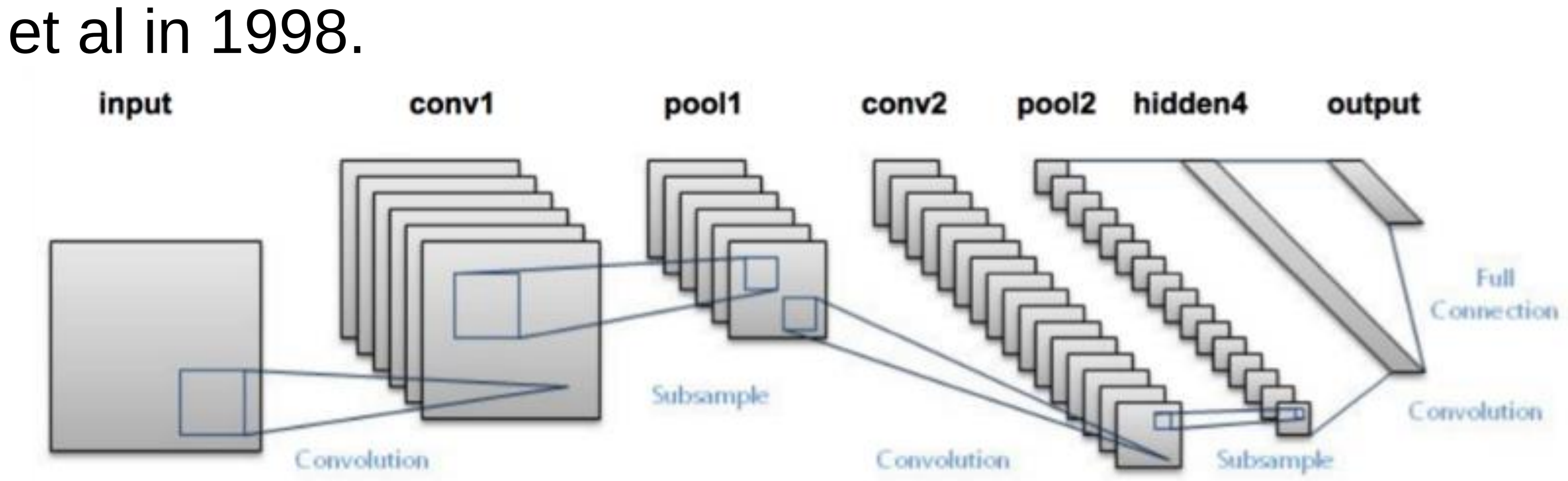
Methodology

First, an anomalous event was defined quantitatively. The definition was changes in intensity exceeding a factor of 100 that took place over a narrow range of frequencies or over a short period of time. These changes also had to be discontinuous from 0 Hz by a measure of at least 50 Hz. This definition was then used to manually label BAS data to create a training data set.

Next, the direct readings from the magnetometer array at the BAS Halley Site were passed through a fast fourier transform using a prebuilt python library (SciPy).

This data was then parsed into three different representations: one that compacted the data into a set of ranges, one that took the log10 of the data, and one that took the log10 of the data and compacted the output of the log10 into a set of ranges.

The data was fed into several different neural network architectures, all of them closely following the structure of the convolutional neural network described by LeCun, et al in 1998.



Methodology, cont…

There were several convolutional neural network architectures utilized. The first was LeNet as specified by LeCun, et al. Another reduced the number of convolutional filters in the second layer. Another removed the second convolutional and max pool layer. Each of these architectures were modified further to drop weights from them at different rates. This dropping of weights was attempted at both layers, only the first layer, and only the second layer.

In each case, a softmax classifier was used along with categorical cross entropy as the loss function. Training was performed using the optimizers Adam and Stochastic Gradient Descent with varying training rates.

Conclusion

The most effective convolutional neural network architecture for the purposes of identifying anomalies in geomagnetic data was the network that utilized the optimizer Adam with a learning rate of .001 to train a network of two convolutional+pool layers, with the weights from the second convolutional layer being dropped at a rate of 50% between training epochs. The most effective structuring of the input data was to compact the transformed data into a set of ranges, with each range spanning 100000 units. Using these hyper parameters, an accuracy of 96% was attained.

References

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