Convolutional Neural Networks for Automated Detection of ULF Waves in Swarm Time Series

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ABSTRACT

Ultra-low frequency (ULF) magnetospheric plasma waves play a key role in the dynamics of the Earth's magnetosphere and, therefore, their importance in Space Weather studies is indisputable. Magnetic field measurements from recent multi-satellite missions (e.g. Cluster, THEMIS, Van Allen Probes and Swarm) are currently advancing our knowledge on the physics of ULF waves. In particular, Swarm satellites, one of the most successful mission for the study of the near-Earth electromagnetic environment, have contributed to the expansion of data availability in the topside ionosphere, stimulating much recent progress in this area. Coupled with the new successful developments in artificial intelligence (AI), we are now able to use more robust approaches devoted to automated ULF wave event identification and classification. The goal of this effort is to use a deep learning method in order to classify ULF wave events using magnetic field data from Swarm. We construct a Convolutional Neural Network (CNN) that takes as input the wavelet spectra of the Earth's magnetic field variations per track, as measured by each one of the three Swarm satellites, and whose building blocks consist of two convolution layers, two pooling layers and a standard NN layer, aiming to classify ULF wave events in four different categories: 1) Pc3 wave events (i.e., frequency range 20-100 MHz), 2) non-events, 3) false positives, and 4) plasma instabilities. Our primary experiments show promising results, yielding successful identification of more than 95% accuracy. We are currently working on producing larger training/test datasets, by analyzing Swarm data from the mid-2014 onwards, when the final constellation was formed, aiming to construct a dataset comprising of more than 50,000 wavelet image inputs for our network.

Data and Methodology

- Data from Swarm magnetic field measurements (total magnitude, extracted from Swarm Magnetic Field Vector, NEC frame, 1s sampling rate), from February to April of the year 2015.
- Segmented into mid-latitudinal tracks (i.e., -45 to +45 deg. latitude), in order to exclude the influence of polar FACs that might affect the measurements.
- Filtered using a high-pass Butterworth filter with a cutoff frequency of 16 mHz.
- Wavelet analysis on the produced time-series. The wavelet spectrum images are then used as the input features in the CNN model.
- Training and test dataset, by dividing the Swarm tracks in 4 classes, namely Pc3 (20 - 100 mHz) ULF wave events, non-ULF signals i.e., background noise without significant wave activity, False Positives (FP), e.g., anomalous signals due to spikes, discontinuities, etc., and Plasma Instabilities i.e., events that are influenced or caused by Equatorial Spread F (ESF) irregularities (Stolle et al., 2006; Park et al., 2013) or in general by other, unclassified anomalies in the ionosphere, in near-equatorial, night-side areas.
- CNN model, consisting of 2 convolution layers, 2 pooling layers and 2 fully connected layers.
  - Convolution Layer: calculates the convolution of the input image with a "filter"
  - Pooling Layer: reduces the size of the image
  - Flattening Process: converts the final multidimensional image to a vector of input parameters
- The Swarm data analysis was implemented using the framework of the Matlab programming environment, while the CNN model was implemented using Python and its open-source platform TensorFlow.

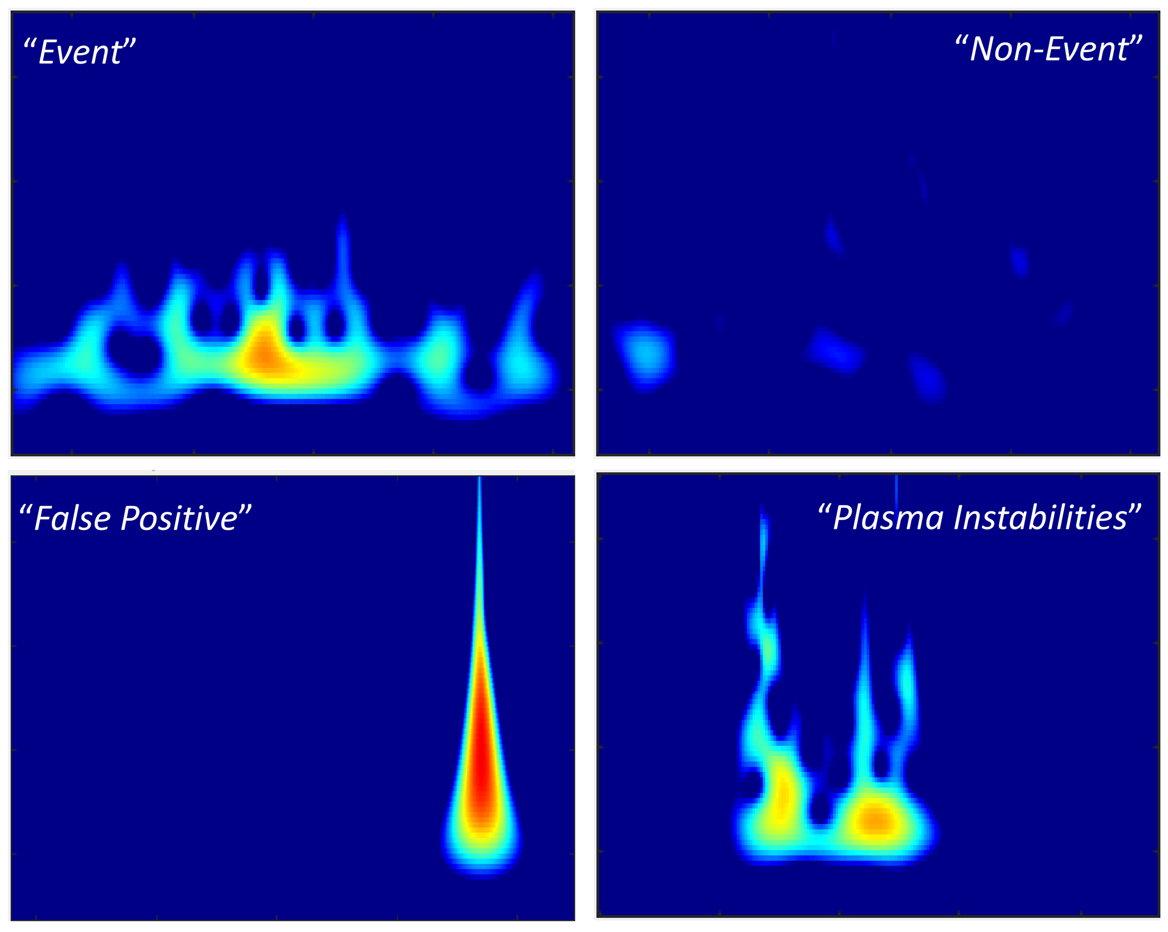

Fig. 1. Examples of the four categories of our classification problem. From upper left: Event, Non-Event, False Positive, and Plasma Instabilities.

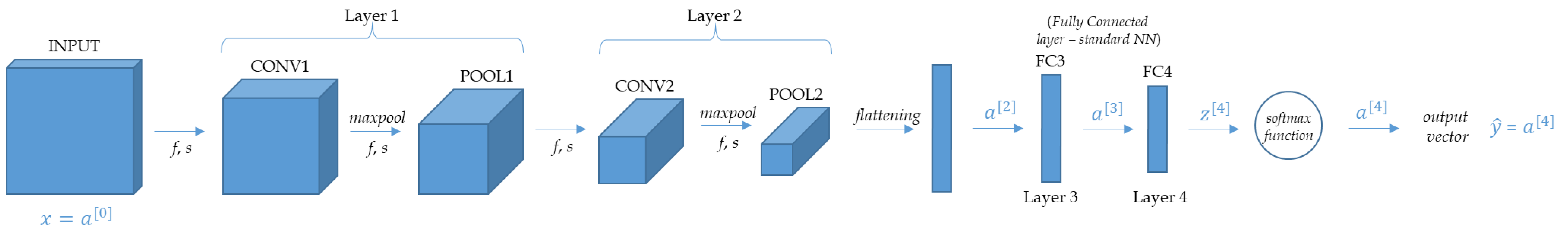

Fig. 2. Schematic representation of the complete deep CNN model, with four layers in total, where the first two consist of a convolution and a pooling process while the last two are fully connected layers. The final fully connected layer results in 4 neurons in the output layer (equals to the number of classes), which then get passed to a Softmax activation function.

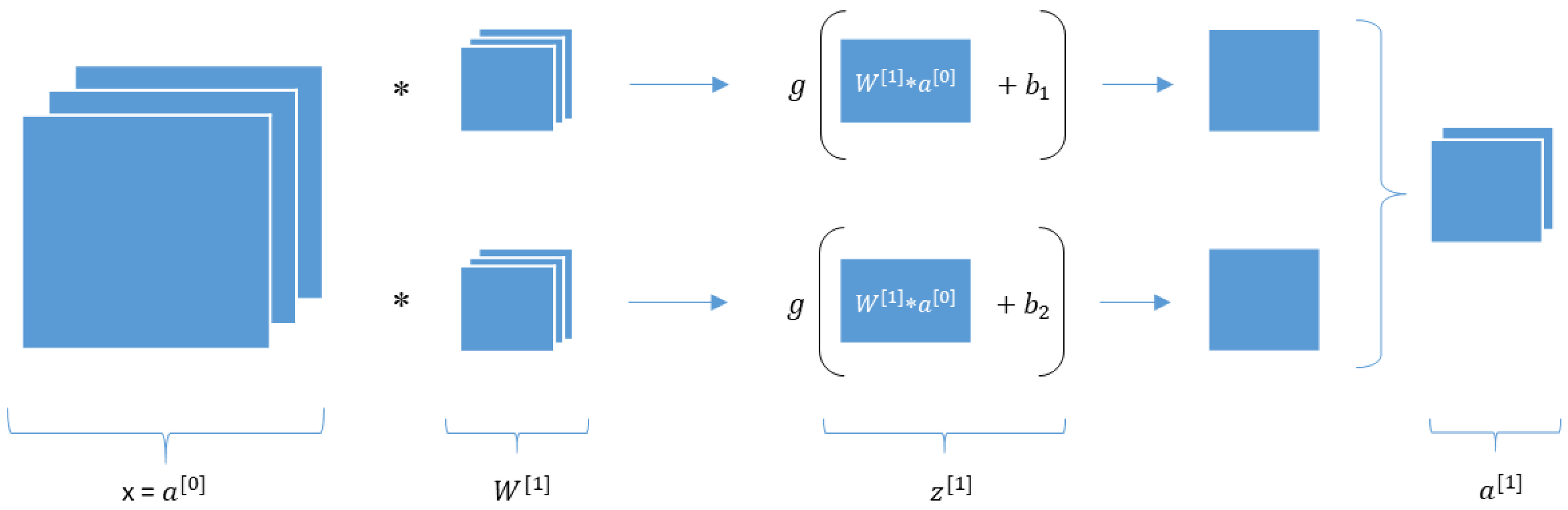

Fig. 3. The CONV1 layer representation: convolves W1's filters on x, adds biases b1, and calculates the ReLU activation function over z1, where $z^{[1]} = W^{[1]}a^{[0]} + b^{[1]}$ and $a^{[1]} = g(z^{[1]}) = \mathrm{ReLU}(z^{[1]})$, with weights W and biases b to be the parameters of our network.

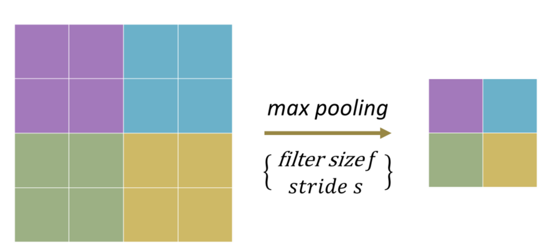

Fig. 4. Representation of the pooling layer: uses a window of size (f, f) and strides of size (s, s) to perform max pooling over each window. Filter size f and stride s are the hyper-parameters of our network.

Table 1. Number of examples for each category. The total number of examples is 2030, of which the 80% was used for the training and the 20% for the test set.

Events	700
Non-Events	680
Plasma Instabilities	550
False Positives	100
Training examples	1624
Test examples	406
Total	2030

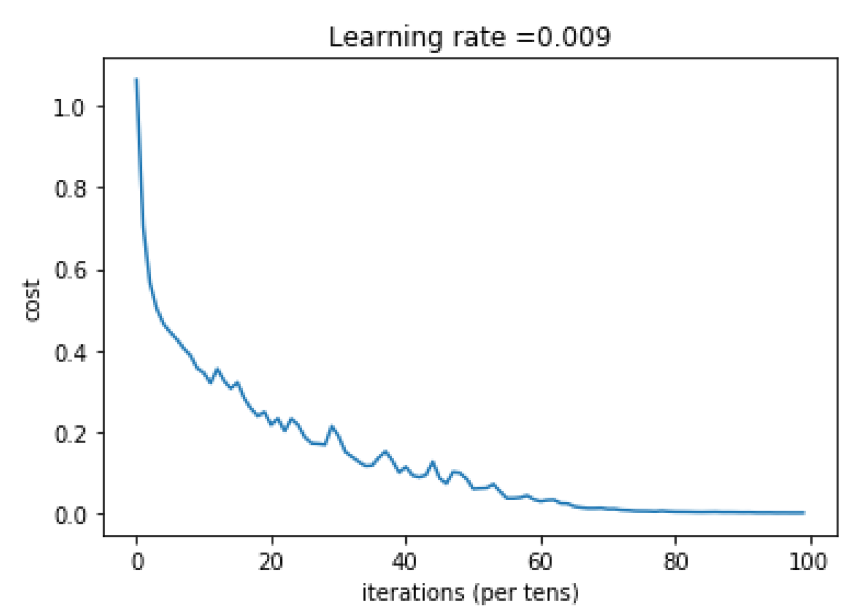

Fig. 3. Plot of the cost function vs the number of epochs of the optimization loop. After 100 epochs of training of the model, the accuracy of the test set is equal to 87.5%

Conclusions

- The CNN model shows promising results, recognizing ULF wave events with almost 90% accuracy on the test set
- Due to the large number of parameters of the model, it is crucial to build much larger training/test sets, of at least 50,000 input features

Future Work

- Introduce regularization in our model in order to avoid high variance
- Improve its accuracy by spending more time tuning the hyperparameters
- Re-training with larger dataset by analyzing Swarm data from the mid-2014 onwards, necessary for optimal performance

References.

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