Adaptive Resonance for Planetary Exploration

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Introduction

One of the most important aspects of autonomous operations is in-situ analysis. This is where autonomous and semi-autonomous platforms perform analysis on data in the field, and either return that analysis to base, or use it to select subsequent actions [1, 2, 4, 7, 8, 10, 11].

Acquiring science and operations data when exploring other planetary bodies is a challenging task, with robotic platforms being a vital option in the hostile environments present in the Solar System.

More complex rovers and drones [11, 17], have made the use of robotic platforms essential, especially where the environment is dangerous or inaccessible to humans.

Method

Dataset

The dataset consists of a variety of Lidar and software generated point clouds, acquired from various areas of geological interest, such as Kilbourne Hole in Arizona and Mokka Fjord in the Canadian Arctic [10].

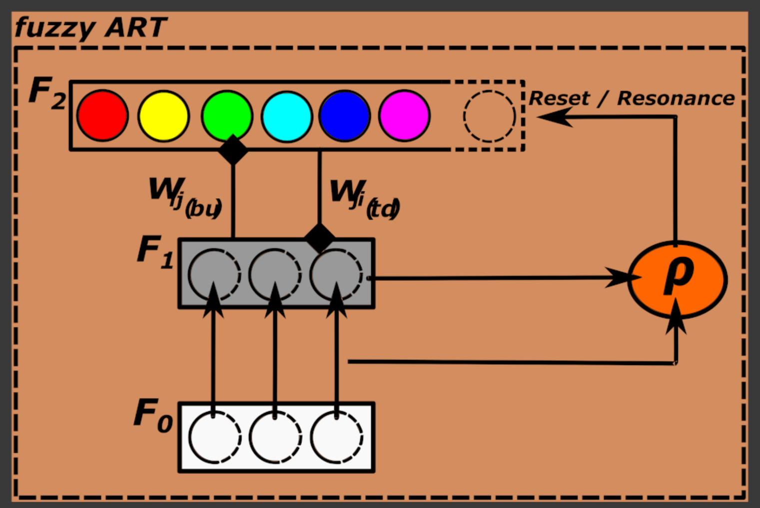


Fig 1. Network diagram of Fuzzy Adaptive Resonance. The diagram shows the three layer structure, connected to the vigilance parameter that controls classification granularity.

Pipeline

A Nearest Neighbours classifier – covariance - eigen decomposition technique[6], that can generate descriptors such as normal vector, curvature and sphericity from spatial coordinates.

Feature extraction network – Adaptive Resonance

The fuzzy ART neural network [3, 9] is used for geological feature extraction. It is a shallow network designed to highlight features of interest with low computational overhead, no training signal and a clustering/classification mechanism that is transparent, making it an interesting candidate for remote autonomous operations.

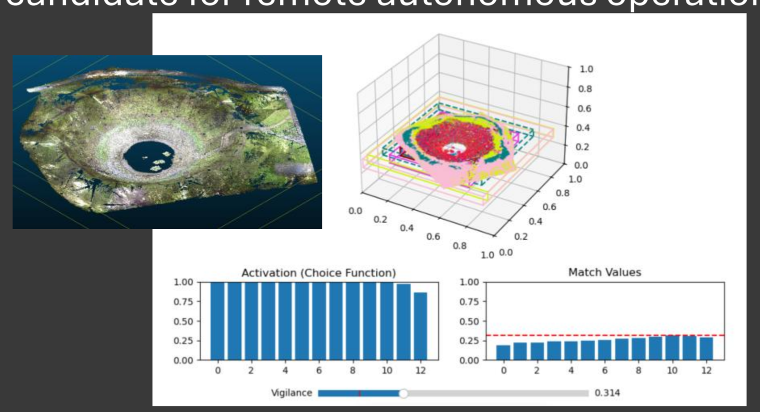
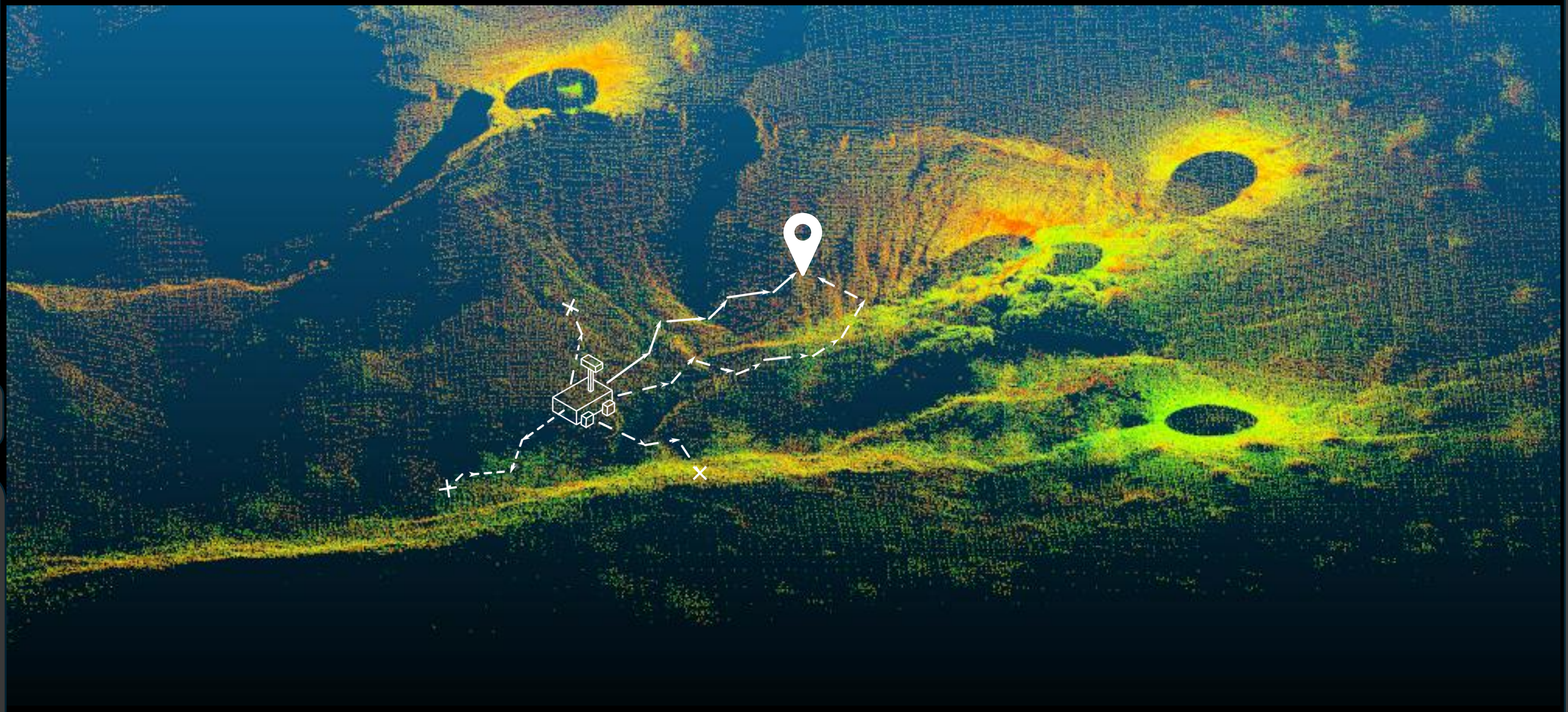


Fig 2. (inset, left) Image of the Kaali crater in Finland, one of the datasets for this work. (main) Image of current fuzzy ART network classifying the Kaali dataset. Each colour represents a different. Here the network identified the crater bowl as an area of interest.



Results

Experiments consisted of running a variety of combinations of feature vectors over each dataset to generate meaningful classifications.

A custom framework was created to pass these classifications first to dimensional reduction, then to metric analysis, to determine which classification is viable, without any human-in-the-loop.

After approx. 13,500 runs on 18 datasets with 15 combinations of feature dimensions, we found that the pipeline consistently selected network classifications that highlighted geologically significant features.

The most successful selections utilised normal vector and normal vector with curvature point descriptors **without** positional (x, y, z) dimensions.

Conclusion

Experimentation demonstrated that it is possible to utilise a low overhead, low footprint neural network for direct volumetric surface topology classification without computationally expensive training or models.

Adaptive resonance's intrinsic attributes regarding computational cost, bias and trustworthiness, make it an interesting choice for future work for autonomous processing in operations in the near and far solar system.

Ongoing Research

This work provides an interesting platform to develop autonomous exploration framework for spacecraft using the components developed here:

Neural Network based feature extraction (Large Scale Perception)

Adaptive Resonance network for macro feature detection: Adaptive resonance has been demonstrated to translate well to a variety of custom, reconfigurable, parallel and edge architectures.

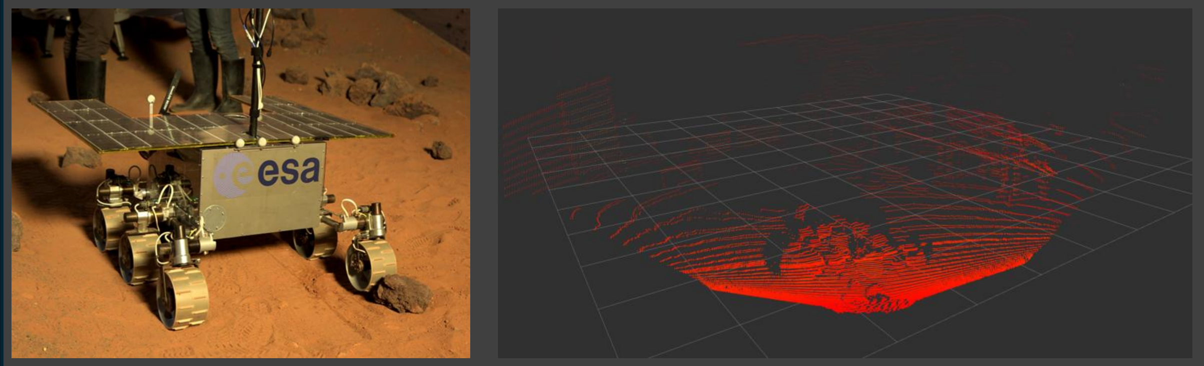


Fig 3. (left) the MARTA rover platform operated at the Planetary Robotics Laboratory at ESA-ESTEC. (right) Output of the Lidar scanning instrument on MARTA viewed through the Rviz ROS interface

Path Planning

Implementation and integration of path finding algorithms such as Rapidly Exploring Random Tree (RRT*) to pathfind between origin point and identified area of interest.

Collision Detection (Local Scale Perception)

Utilisation of statistical ML techniques to provide local context perception. The nearest neighbour-eigen decomposition method will be used to extract additional dimensional vectors from generated point clouds of the current path.

With accurate normal vector generation, obstacles can be identified through deviations from [roughly] nadir pointing vectors (ground). Geological attitude measurements can be generated from normals with high accuracy.

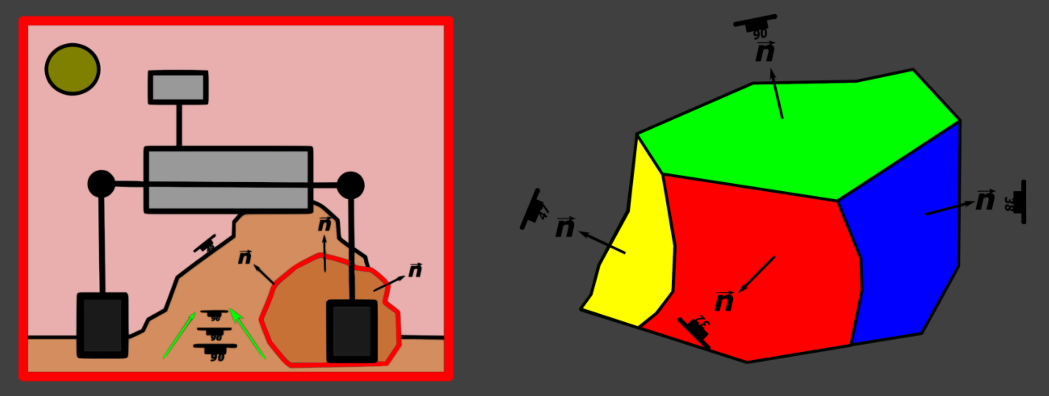


Fig 4. (left) Collision detection will use ML techniques to extract normal vectors from points and transform them geological attitude measurements. (right) This can enable simple command logic for traversal and identification of obstacles/targets for instrument sensing

This should enable complex operational logic to be embedded command sequence instructions[1] using simple geological attitude measurements.

References

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