INTERNATIONAL SPACE APPS CHALLENGE

SISMOTXNY: MULTI-PLANETARY SEISMIC DETECTION SYSTEM BASED ON DEEP LEARNING AND ENSEMBLE

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1. INTRODUCTION:

Planetary seismology faces difficulties in efficiently transmitting seismic data from celestial bodies such as the Moon and Mars to Earth, due to the high energy demand required to transmit large volumes of data, especially when dealing with more distant celestial bodies. Since only a fraction of this data is scientifically useful, a potential solution is the implementation of algorithms that allow for the autonomous detection of significant seismic events and the exclusive transmission of this data.

This project aims to develop a program capable of identifying seismic events in planetary records from missions such as Apollo and InSight, differentiating useful signals from noise. This would not only optimize data transmission to Earth but also make more efficient use of the limited resources of landing modules. The implementation of machine learning approaches and conventional algorithms adapted to the planetary context presents significant potential for improving the quality of seismic data received from other bodies in the Solar System.

This report details the methodological approach and technologies that will be used to address this challenge.

2. THEORETICAL BASIS:

Planetary Seismology

Planetary seismology studies vibrations or ground motions caused by natural or artificial sources on planetary bodies other than Earth, such as the Moon or Mars. These vibrations provide valuable information about the internal structure of planets, their tectonic activity, and other geophysical phenomena. Unlike terrestrial seismology, planetary missions face technical challenges, such as limited data transmission due to the distance between the planet and Earth, and low signal-to-noise ratio in the collected seismic data (Giardini et al., 2020;

Lognonné & Johnson, 2015). Landing modules, like InSight on Mars, collect data from highly sensitive seismometers, which can detect both seismic signals and environmental noise, making the identification of seismic events challenging (Lognonné & Johnson, 2015).

The Apollo missions provided the first seismic data from the Moon, and the InSight module has been the first to provide continuous data from Mars. These data have allowed the identification of seismic events, known as moonquakes and marsquakes, respectively. However, the extraction of these signals requires thorough analysis and advanced techniques to discern useful signals from ambient noise and instrumental interference (Oberst et al., 2012; Teanby, 2015).

Seismic Signal Processing

Signal processing is essential in planetary seismology due to the high presence of noise. Techniques such as the Fourier Transform (FT) and Short-Time Fourier Transform (STFT) allow transforming time-domain signals to the frequency domain, facilitating the identification of relevant patterns (Aster et al., 2018). These spectral analysis methods enable the study of seismic wave frequencies and the differentiation between noise and significant seismic events (Aster et al., 2018).

The Short-Term Average/Long-Term Average (STA/LTA) algorithm is a widely used method for the automatic detection of seismic events. This algorithm compares the energy in short and long time windows to detect significant changes in the signal, allowing the identification of potential quakes (Withers et al., 1998). However, the standard STA/LTA may be insufficient in low signal-to-noise environments, requiring improvement or complementation with more sophisticated techniques (Withers et al., 1998).

Machine Learning in Seismic Detection

Machine learning (ML) has emerged as a key tool for the classification and detection of seismic signals in planetary research. Convolutional Neural Network (CNN) models have been successfully used for pattern classification in spectrograms generated from seismic data (Perol et al., 2018). These convolutional networks can capture complex spatial features of signals that may go unnoticed by conventional methods (Perol et al., 2018).

The use of ensemble techniques, which combine multiple algorithms, is an effective strategy for improving the performance of seismic detection models. Models like XGBoost and Random Forest can leverage statistical features of signals, such as their variance and energy, providing a complementary view to the CNN-based approach (Chen & Guestrin, 2016). These hybrid approaches maximize detection capability by combining supervised methods with automatic feature extraction, achieving greater accuracy and robustness against planetary noise (Ross et al., 2018).

3. METHODOLOGY:

The proposed methodology for the seismic event detection project on Mars and the Moon will be structured into several phases. First, the seismic data will be read from the corresponding files, and the velocity records will be combined with information from the seismic event catalog. This will allow the generation of a labeled dataset that will serve for the creation and evaluation of the models. Then, the data will be divided into training and validation sets to ensure proper model preparation.

In the preprocessing phase, bandpass filters will be applied to highlight the relevant frequencies of seismic events. Additionally, spectrograms will be generated using the Short-Time Fourier Transform (STFT) to analyze the time-varying frequencies. Statistical features of the seismic signals, such as mean, variance, skewness, kurtosis, and energy, will also be extracted, allowing for a more structured representation of the data.

The model development will include several approaches. First, an improved STA/LTA (Short-Term Average/Long-Term Average) model will be implemented, adaptively adjusting its thresholds to optimize its performance under noisy conditions. Subsequently, a Convolutional Neural Network (CNN) will be designed to process the generated spectrograms, extracting patterns through convolutional and pooling layers, while the fully connected layers will handle the classification. An ensemble approach will also be developed, combining the improved STA/LTA model, the CNN, a Gradient Boosting model (XGBoost), and a Random Forest model, to improve the overall accuracy of the detection system.

Regarding training and optimization, cross-validation will be employed to tune the hyperparameters of the models, and regularization techniques will be used to prevent overfitting. Early stopping will be implemented to determine the optimal number of epochs for model training, preventing a loss of generalization.

Finally, the system evaluation will be carried out. Metrics such as accuracy, recall, F1-score, and the AUC-ROC curve will be used to measure the performance of the models, while the temporal difference between predicted and actual detections will be calculated to evaluate the temporal accuracy of the system. Subsequently, the trained model will be applied to the test data, including records from the Apollo 12, 15, 16 missions and the records obtained by InSight, generating an output catalog with the obtained results in the required format for final analysis.

4. REFERENCES:

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