Project report: NASA Space apps Challenge

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October 5-6th 2024

Chosen challenge: Seismic Detection Across the Solar System

Introduction

As the time goes on it unfortunately seems that humankind's migration to our nearest and most habitable planet, Mars, is almost imminent; thus planning the future settlement location on such planet its a task that has taken up relevance around the astronautical community worldwide, we firmly believe that our findings on this challenge could be very useful towards this global effort.

We are machine learning enthusiast, and we got truly immersed on seismology throughout the hackaton.

During the development of the project we found out that there were several noise-causing factors that potentially disturbed the insight´s seismometer lectures such as:

- Atmospheric pressure fluctuations on Mars surface.
- Variations on the wind fields, transmitting vibrations trough the insight´s dome
- The brownian effect on the instrumentation that causes noise in the range of (0.5-1.0)(Hz).
- Electromagnetic noise caused by the solar wind or the triboelectric effect.

While we were reviewing the ways we measure seismicity on earth, locating the instrumentation underground in order to mitigate atmospheric noise couldn´t be done on Mars since the seismometer is deployed on the surface making it susceptible to the noise sources mentioned above.

Our first approach

Given the first training data sets: XBELYSE02BHV20220102HR04evid0005.

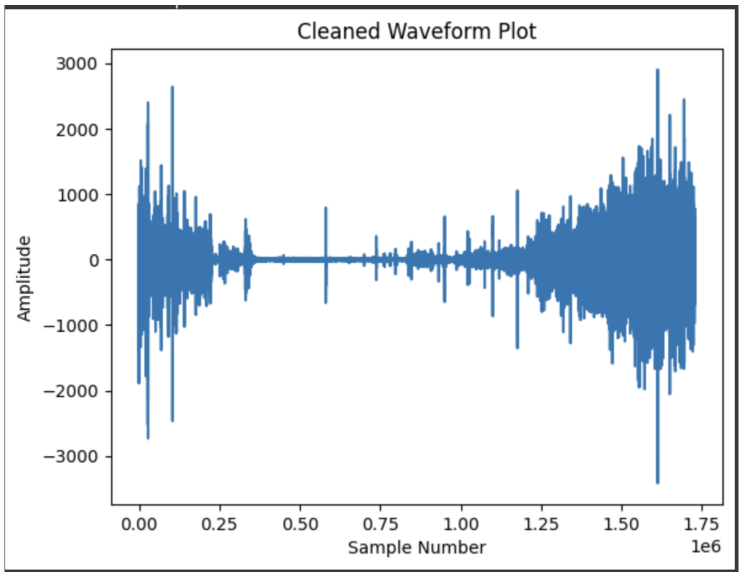

Figure 1: Cleaned waveform

We decided to implement a very simple detection method in which we set a threshold for spikes in data. If the datapoint is beyond the threshold we consider it a quake event. We determined that it was not precise enough since we can clearly observe that there are still several spikes that not necessarily implied that there was a marsquake.

Understanding the data

To begin our machine learning approach we quickly noticed that we had to understand the data distribution since it wasn´t feature rich and we didn´t have an explicit expected value for a quake. We made a histogram of velocity lectures and we found out that it followed a normal distribution (Figure 2.) which makes it valid to use the expression for such data distribution were the expected value is clearly cero and "k" is an integer times standard deviation, in our case k=2 contains approximately 95 percent of the data.

$$\mu \pm (k\sigma)$$

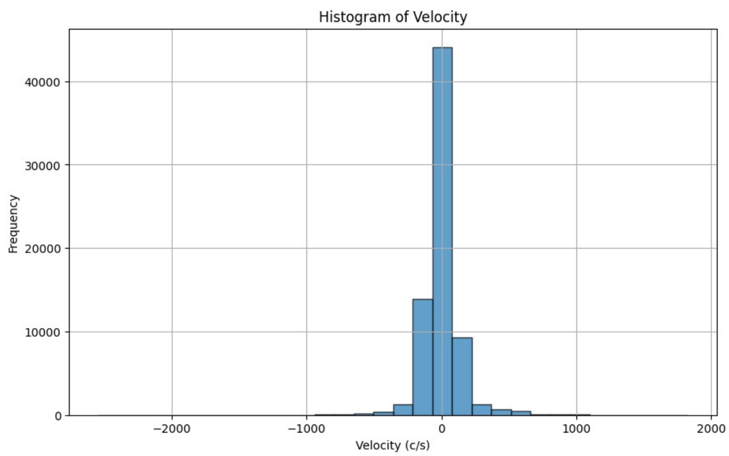

Figure 2: Histogram of velocity

The K-Means algorithm iteratively assigns each datapoint a "k" group, based on its characteristics. They are grouped with their most similar datapoints. We consider it would be wise to use it as it would group readings together so we could determine which cluster is composed by quake datapoints. As far as we developed, there isn't a seamless way to select the number of clusters to use, so we used the Elbow method. The algorithm successfully separated the data into clusters. It's easy to visualize that cluster number 4 could be composed of a quake event. For this particular dataset, we had knowledge on what the quake event was (relative time of 507 seconds, a frequency of 36.5732 c/s).

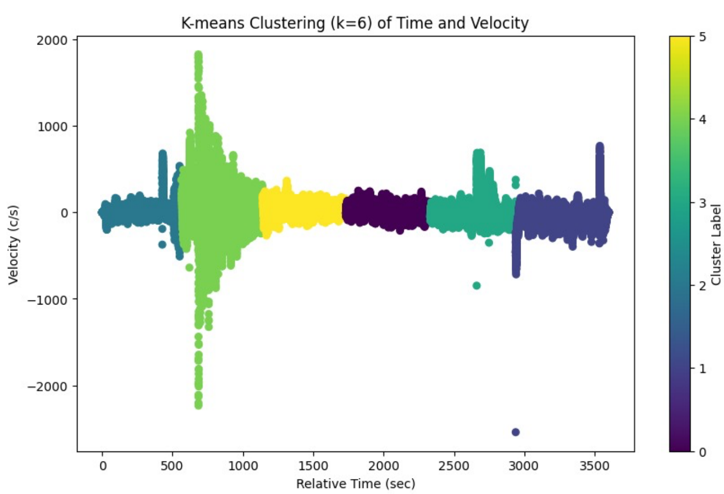

Figure 3: K-means clustering plot

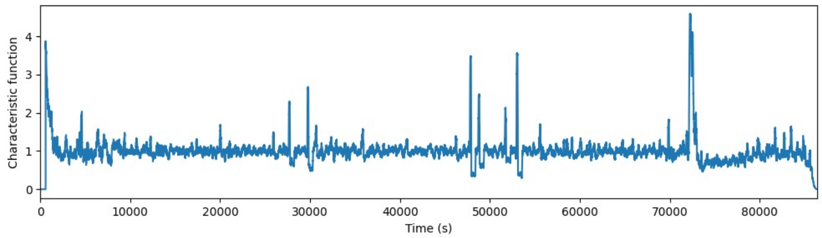

Figure 4: Raw lunar seismic data plot

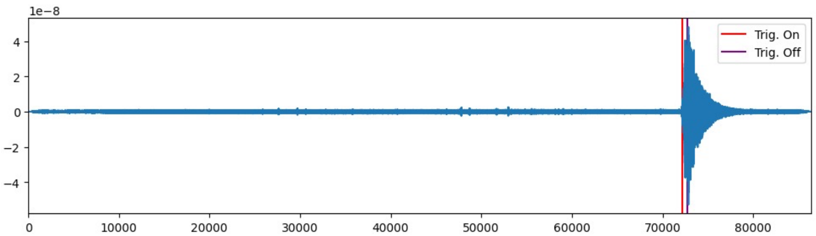

Figure 5: STA/LTA Moon lectures

Comparing lunar an martian lectures

Lunar data was significantly better in terms of analysis since we only had to apply the first STA/LTA algorithm to get a truly smoothed-out original plot and we can clearly see when the incident took place.

Noise reduction through energy maximization

There is a very clever method of optimization that allows us to focus on the longitudinal components of the marsquakes that are the main subject of study on the insight´s mission since it provides information on the composition of Mars; the demonstration of it is not so trivial but it's simultaneously understandable if you have grasp on calculus and rotation matrices .

0.1 Rotation of the components

First of all we´ll rotate with respect to the W component such that the U component maximizes this guarantees that the event energy is only contained on the (U,W) plane. Then We´ll do the same but with respect the V component ensuring that W maximizes. We now have a two one-dimensional optimization problem.

0.2 Energy on rotated components

For this method we are going to express each wave energy component with two angles phi and theta: V component is expressed with respect the azimut angle phi:

0.3 Maximization of Energy

Extremes of energy as a function of the rotation angle

A simple way to minimize energy, having the expressions 3.2 and 3.4, is to find the extremes through their derivatives, which can be found analytically. The energy function defined in equation 3.2 can be rewritten as follows:

$$E_V(\phi) = \cos^2\phi \sum_i U_i^2 + \sin^2\phi \sum_i V_i^2 + 2\sin\phi\cos\phi \sum_i U_i V_i. \tag{1}$$

The summations $\sum_i U_i^2 = E_U^{(0)}$ and $\sum_i V_i^2 = E_V^{(0)}$ are the energies of the components U and V, respectively, prior to rotation. On the other hand, considering that $2\sin\phi\cos\phi = \sin 2\phi$, equation 3.5 can be rewritten as:

$$E_V(\phi) = E_U^{(0)}\cos^2\phi + E_V^{(0)}\sin^2\phi + \sin 2\phi \sum_i U_i V_i. \tag{2}$$

Understanding that $E_U^{(0)}$, $E_V^{(0)}$, and $\sum_i U_i V_i$ are constants with respect to ϕ (since they use samples prior to rotation), the derivative can be calculated simply as:

$$\frac{dE_V}{d\phi}(\phi) = E_U^{(0)} 2\cos\phi(-\sin\phi) + E_V^{(0)} 2\sin\phi\cos\phi + 2\cos 2\phi \sum_i U_i V_i. \tag{3}$$

Finally, the angle satisfies this condition:

$$\phi = arctan(\frac{2\sum qiUiVi}{E(0)UE(0)V})$$

analogically:

$$\theta = arctan(\frac{2\sum qiUiWi}{E(0)UE(0)W})$$

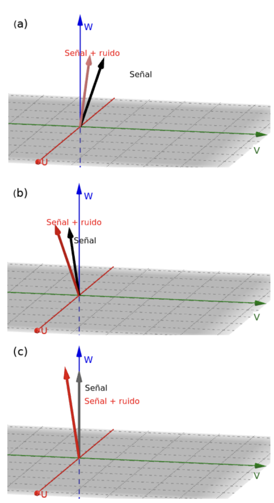

Figure 6: Rotation diagrams

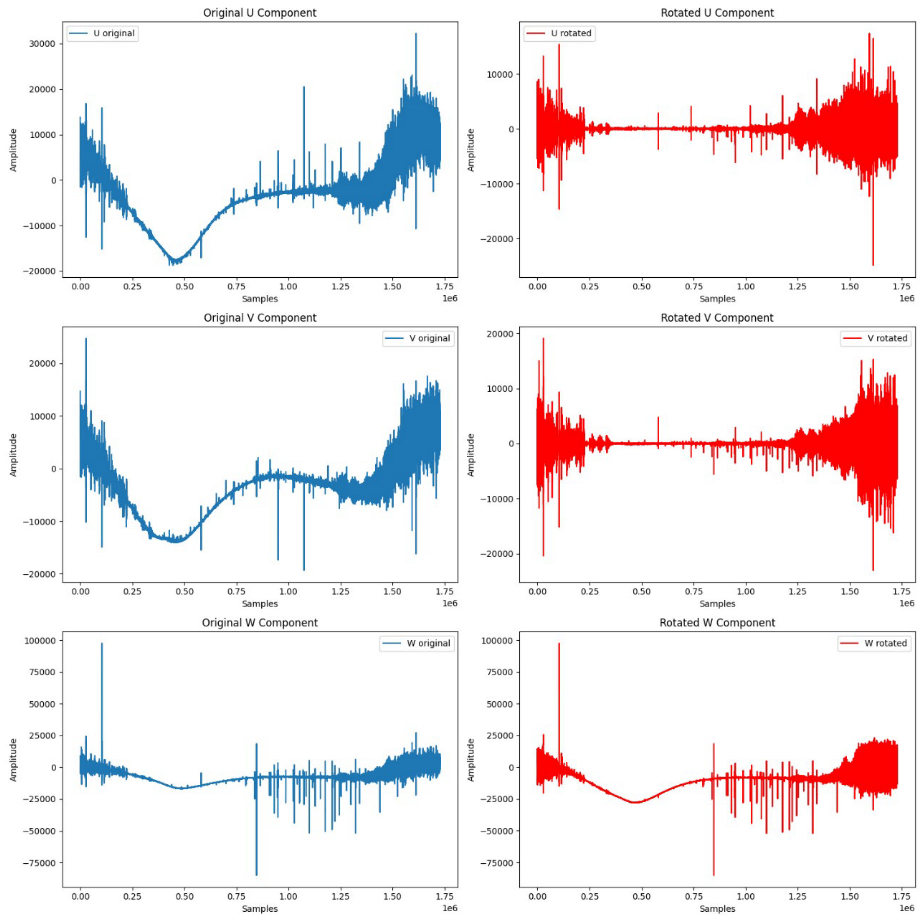

Figure 7: Noise attenuation plots using optimization/rotation

So we applied this transformation on the seedfiles from the BHU, BHV, BHW waveform amplitude components retrieved from SEIS PDS geoscience repository, this were our results:

Future Work

After diligent research we've found a paper by PhD. Sergey Pulinets (2022) that uses atmospheric gas concentration changes to predict future earthquakes; while earthquakes and marsquakes are caused by differing factors, the common cause for gas release is the fracturing of the crust in which earthquakes release Radon. While Radon is less abundant on Mars, methane could be very much be present in the martian crust; Murray, J Jagoutz, O. (2024) present a possible reason as to how Mars' atmosphere could have turned into methane after researching the process in which the atmosphere was transformed into methane and stored in the crust.

The early Martian atmosphere had 0.25 to 4 bar of CO2 but thinned rapidly around 3.5 billion years ago. (Murray and Jagoutz, 2024). However, Mars' current CO2 measures in the atmosphere suggest a substantial loss of CO2. The possible difussion of this compound are to space or to Mars´ lithosphere. It is speculated that while it existed water on Mars' surface, this liquid could be leaked into certain rocks as *Olivine* which set off reactions that extracted CO2 as a timed process which end turning into Methane, which could be trapped under Mars' crust.

The idealized chemical equation of the proposed process is shown as:

$$\textit{Olivine}\,(Fo_{68}) + H_{20} + CO_2 \longrightarrow \textit{Serpentine} + \textit{Magnetite} + CH_4$$

$$(Mg, Fe)_2\, Fo_{68} + H_2O + CO_2 \longrightarrow Mg_3Si_2O_5(OH)_4 + FeO\ \cdot Fe_2O_3 + CH_4$$

(A) On the other hand, Insight Lander is located on Elysium Planitia, where also Cerberus Fossae is shown. This co-relates seismic activity due to the active fault in the Fossae.

(B) This map shows Mars major faults, highlighting the Cerberus Fossae. Extensive faults are shown in red, while compressive faults are shown in aqua-marine.

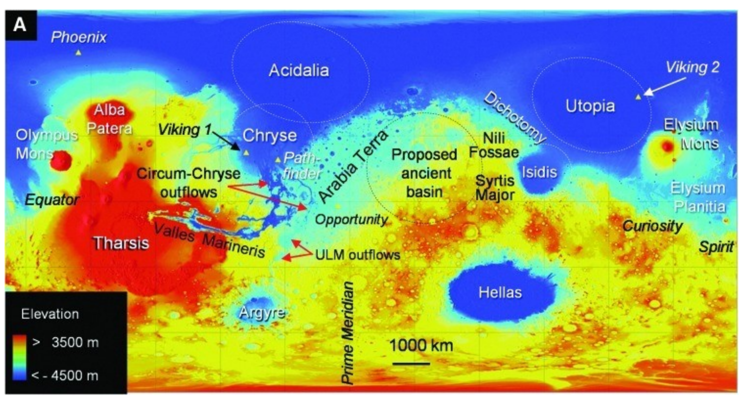

Figure 8: Mars elevation map

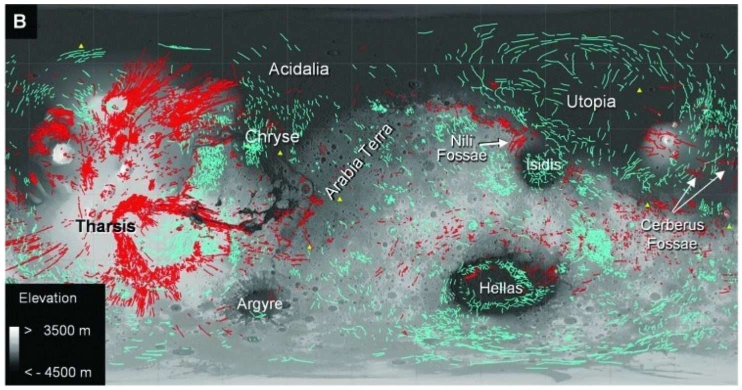

Figure 9: Mars major faults map

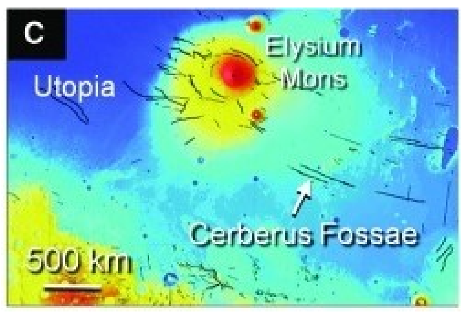

Figure 10: Cerberus Fossae faults

(C) The area of Insight Lander is shown. Remarking elevation and faults in the zone.

Lack of processed data makes modeling and simulation unviable for this project. Nevertheless, data obtained from orbiters such as Mars Express and MRO can be used for the proposition of a mathematical equation. On the other hand, new satellites and constellations can be crucial for future manned missions and seismic monitoring and prediction.

The representation of a mathematical model for the Methane concentration change in time can be expressed by:

$$dC/dt = P–L - D$$

- C: Methane concentration in an specific point on the atmosphere.
- P: Methane production rate caused by the release from the fault.
- L: Methane loss rate due to oxidation processes.
- D: Methane difussion rate to the atmosphere.

While the enlarged Partial Differential Equation can be proposed as:

$$\frac{\partial C}{\partial t} = \nabla \cdot (D \nabla C) + Q(x, y, z, t) - kC \tag{4}$$

- • ∇: Nabla operator (gradient)
- • D: Diffusion coefficient of methane in the porous medium (can vary with depth and water saturation).
- • Q(x,y,z,t): Source term describing the rate of methane production due to faulting and earthquake.
- • k: Rate of methane loss due to oxidation processes and other sinks.

Finally the breakdown of the Source Term describing the rate of methane production is:

Where:

$$Q(x, y, z, t) = f(M, t_s) \cdot g(z) \cdot h(x, y) \cdot P_m$$

- • $f(M, t_s)$: Function that relates the magnitude of the earthquake (M) and its duration (t_s) to the amount of methane released. This function could be empirical or based on rock fracturing models.
- • $g(z)$: Function that describes the distribution of methane at depth, considering the percentage of trapped methane and the permeability of the rocks.
- • $h(x, y)$: Function that describes the spatial distribution of the fault.
- • P_m : Methane pressure in the rock pores.

Conclusion

A good way to save energy is by sending only the bits of information that is more likely to correspond to a marsquake and that does correspond to NASA, developing this predictive model alongside the algorithms to cleanse the signals noise and thus taking advantage of the energy for other tasks; this would signify more accurate prediction models on planetary seismology and in consequence this would improve the chances of colonizing the martian surface.

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