EGU21-12344
https://doi.org/10.5194/egusphere-egu21-12344
EGU General Assembly 2021

Atmospherically driven ground motion at InSight: a machine learning perspective

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The NASA InSight lander is a geophysical and meteorological observatory operating on Mars for over a Martian year/two Earth years. Continuous records of seismic, pressure, wind and temperature data over this period have led to significant breakthroughs in determining the planet's structure and climate. With such a wealth of data now received, machine learning offers a nascent tool to extract further information.

The seismic data is extremely correlated to the atmospheric conditions. Discerning the coupling between the atmosphere and ground motion is of significant interest and this work aims to predict the ground motion generated by wind and pressure forcing using machine learning techniques. From this prediction we can untangle the various contributions to ground motion, determine atmospheric/ground properties, analyse/discriminate marsquakes and potentially decorrelate waveforms to remove the atmospheric contribution. While a physical model for this atmospheric forcing is desirable, machine learning approaches the problem from an alternative view point where mathematical and algorithmic tools add the necessary complexity for fitting the data. In this way, we may be able to capture detailed variation and inform further modelling efforts.

We will detail the initial application of machine learning for predicting the ground motion from the atmospheric data inputs of wind speed, wind direction, pressure and temperature. First though, we will describe the issues that need to be tackled to obtain a good prediction using the InSight data. To illustrate some of some of these problems, consider that glitches are known to occur in the seismic data. They offer a way to detect overfitting as they should not in general be predicted

from atmospheric forcing. However, a subset of the glitches are correlated to temperature on top of the fact they are only visible during quiet enough periods, as are marsquakes. Therefore, they are not a normally distributed source of noise or uncorrelated from the input atmospheric data, breaking typical assumptions used for regression. A similar issue is presented by the changing weather conditions throughout a Martian sol, where the time series distribution varies. As a result, prior information on the instrumentation and data qualities is essential for applying the machine learning methods and interpretation of the results.

We demonstrate the specifics of the InSight data with respect to 1) how a curve fitting problem can be constructed, 2) the necessary degrees of freedom of the problem, 3) consideration of non-stationary/heteroscedastic errors and 4) the optimisation and machine learning method applied. Current results will be presented from the implementation of random forests and gaussian processes. These results demonstrate a good performance so far for capturing the global variation and we will offer perspectives on how these results can be used and improved.