A MACHINE LEARNING APPROACH FOR ESTIMATING ASTEROID SURFACE PROPERTIES FROM ACCELEROMETER MEASUREMENTS. A.Duchêne[1], J.Segovia Otero[1], N.Murdoch[1], M.Drilleau[1] and A.Stott[1], [1]Institut Supérieur de l'Aéronautique et de l'Espace (ISAE-SUPAERO), Toulouse, France (alexia.duchene@student.isae-supaero.fr).

Abstract: The mechanical properties of small body surfaces can be estimated from accelerometer measurements of spacecraft landings. Here we implement and test, using a large database of experimental data, a probabilistic approach with a Machine Learning algorithm to first predict, and then interpret, accelerometer data.

Introduction: During the past decade, there have been many small body missions targeting asteroids such as the Origins-Spectral Interpretation-Resource Identification-Security-Regolith Explorer (OSIRIS-REx) mission [1], the Hayabusa-2 mission [2], and the recently launched Double Asteroid Redirection Test (DART) mission [3]. Understanding the surface interactions helps to reduce the risk of space missions with lander components, but the landing event itself can actually be used for scientific studies of the asteroid surface properties. As asteroids are often covered by regolith [4], landing can be studied as a low-velocity impact onto granular material under reduced gravity conditions. However, it is important to investigate and understand the link between surface properties and the landing behavior.

Experimental Set-up: Experimental trials have been conducted (with the terrestrial gravity set-up shown in [5], and Fig.1).

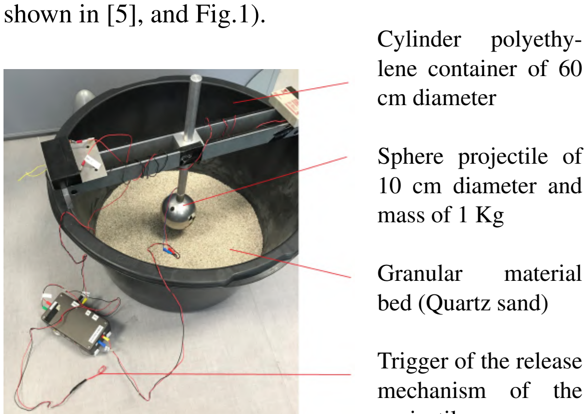

Figure 1: Terrestrial gravity set-up to study impact onto granular material.

Accelerometers have been attached inside the projectile at the center of its mass to obtain the acceleration profile during the collision of the projectile dropped onto the granular surface. The granular materials that have been used are quartz sand, and three different sizes of glass beads (1.5, 5 and 10 mm diameter). All the materials have been characterized by computing their different properties: angle of repose tests to infer the internal friction angle, the grain diameter, the coefficient of sphericity (height divided by the length), the factor of angularity, the roughness, and the bulk density measured for each trial. Two types of projectiles have been used: spherical, and cubic (face, side and corner position). The impact database now contains data from more than 300 experimental trials, with collision velocities between $0.23\ m.s^{-1}$ and $2.15\ m.s^{-1}$.

As the impacts of landers are in reduced gravity conditions for space missions, it is important to note that this changes the dynamics of the projectile. In [6], a Froude number scaling has been shown to be successful: an Earth-gravity impact presents the same behavior as a reduced gravity impact, if those have an equivalent Froude number.

Distinguishable acceleration profile: The shape, duration, amplitude and frequency of oscillations of the acceleration profile obtained from the accelerometers are highly dependent on the granular material (see Fig.2).

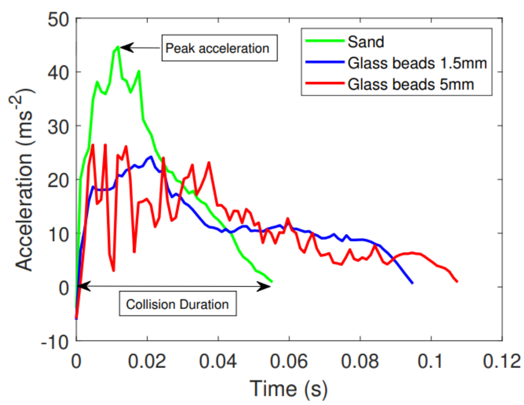

Figure 2: Example of different acceleration profiles during landing with the sphere projectile done for a collision velocity at $1.15\ m.s^{-1}$.

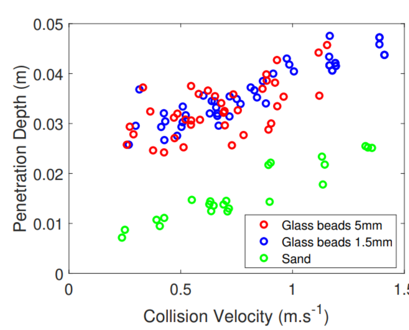

Figure 3: Penetration depth as a function of the collision velocity at impact for all trials with the sphere projectile.

From the double integration of the acceleration profile (example shown in Fig.2), the distance traveled by the projectile can be obtained. Therefore, after impact, the depth can be deduced (shown in Fig.3). For larger collision velocities, the projectile penetrates deeper into the material. The penetration depth also depends on the kind of material the projectile is dropped into - the depth is shallower for a denser and higher friction material such as sand.

Machine Learning algorithm: We have developed a Machine Learning tool to estimate the surface properties of granular material from a single recorded acceleration profile. This is a complementary to the approach of using a physical collisional model [6, 7], consisting in a force law with a depth-dependent static force and a velocity-dependent inertial drag. This tool uses Random Forests from the Scikit-learn Python library [8] as a Machine Learning algorithm. First we develop the *forward problem* to predict the characteristics of the acceleration profile from known surface properties. Then we use the *inverse problem* to estimate the surface properties from the acceleration profile.

Forward problem results: Inputs for the algorithm are the collision velocity and the surface properties during the experimental trials such as the granular material bed height, the grain diameter, the bulk density and the internal friction coefficient. The outputs are predictions of the peak acceleration, the collision duration and the maximum penetration depth. In our approach Random Forests solve a regression problem by splitting the data into training and testing sets. First of all, the training data is used to fit the Random Forest model and then the testing data is used to evaluate the tool's performance. The testing set size is defined as 25% of the available data.

Performance assessment of the Machine Learning algorithm gives values of the coefficient of determination R^2 of 0.95, 0.68, 0.92 for the collision duration, maximum penetration depth and peak acceleration, respectively ($R^2 = 1$ is the best possible score outcome; see [8] for the details). This means that, while the algorithm predicts the collision duration and the peak acceleration with a good level of confidence, it has a harder time estimating the maximum penetration depth. Fig.4 shows the true and the estimated values of the peak acceleration and the collision duration from the training data set. The algorithm successfully differentiates between the different types of material.

We find that the dominating parameters influencing the collision behavior are the collision velocity and the internal friction coefficient, as expected from previous studies [e.g., 5, 7].

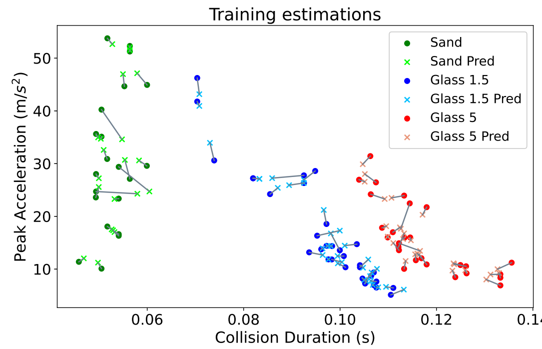

Figure 4: True values (circles) and values estimated from Machine Learning (crosses) of the peak acceleration and the collision duration. Lines join every true and estimated pair.

Conclusion and future work: We have implemented and tested a Machine Learning algorithm to predict and interpret accelerometer data. The algorithm predicts the collision duration and the peak acceleration with a good level of confidence, but the performance estimation is lower for the maximum penetration depth. Machine Learning is a promising technique to approach the problem of estimating the acceleration profile from the surface properties and the collision velocity. Results for the inverse problem in which we estimate the surface properties from the acceleration data will be shown during the conference.

This tool strongly depends on the quality and quantity of the available data; a better and more reliable estimator can be obtained by using a wider variety of granular materials and projectiles. This way, we will be able to better identify the surface properties for future missions such as Hera [9] and the MMX rover [10].

Acknowledgements: The authors acknowledge funding support from the French Space Agency (CNES) and from the European Union's Horizon 2020 research and innovation program under grant agreement No 870377 (project NEO-MAPP).

References: [1] Lauretta D. et al. (2017) *Space Sci. Rev.* [2] Watanabe S. et al. (2017) *Space Sci.Rev.* [3] Cheng A. et al. (2018) *Planet. Space Sci.* [4] Murdoch N. et al., *Asteroid Surface Geophysics*, *University of Arizona Press* (2015). [5] Murdoch N. et al. (2017) *MNRAS*. [6] Sunday C. et al. (2021) *A.& A.* [7] Murdoch N. et al. (2021) *MNRAS*. [8] Pedregosa F. et al. (2011) *J. Mach. Learn. Res.* [9] Michel P. et al. (2018) *Adv. Space Res.* [10] Michel P. et al. (2022) *Earth, Planet. and Space*.