Mars Winds Data Analysis Based on Uncertainty Quantification, Gaussian Process, and Time-Series Forecasting Techniques

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Dates: March to August: 4 to 6 months, ~670€/month

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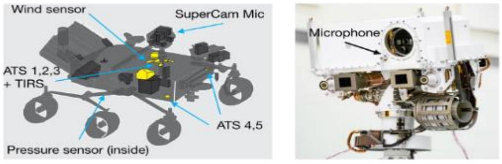

Figure 1. (Left) Diagram of the Perseverance rover with the locations of instruments used highlighted. (Right) Picture of the mast head housing the SuperCam instrument with the microphone location indicated. Credits NASA/JPL-Caltech for the right image, adapted from Maurice et al. (2021), Mimoun et al. (2023).

Figure 1: The wind measurement system on the Perseverance rover on Mars.

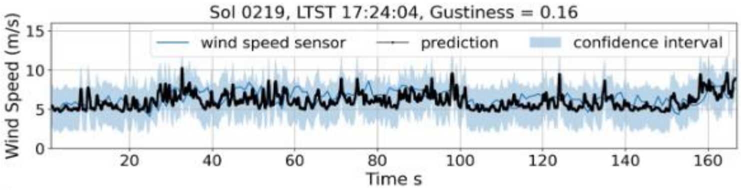

Figure 2: Wind measures in a previous study [1].

As part of several research projects in partnership with industry, ISAE-SUPAERO and IRIT are developing innovative methods for analyzing and interpreting high-frequency atmospheric data from Mars, with a focus on turbulence, wind speed estimation, and time-series modeling. This research leverages Gaussian process regression, uncertainty quantification, and advanced surrogate modeling techniques to address the challenges of sparse, noisy, and expensive-to-evaluate datasets [2]. The ultimate goal is to improve our understanding of Martian atmospheric dynamics and to inform future planetary exploration missions.

Skills

- Mastering of Scientific Computing, Python programming
- Knowledge of machine learning, particularly Gaussian processes
- Understanding of uncertainty quantification and time-series analysis
- Interest in planetary science or in atmospheric modeling, Physics background

Scientific challenges

The scientific challenges of this internship include the development and implementation of robust techniques for uncertainty quantification (UQ) to assess the reliability of wind speed predictions and turbulence estimates, particularly when dealing with sparse or noisy Martian data [3]. A significant focus will be on time-series analysis of high-frequency wind data (e.g., 100 Hz) to extract insights about turbulence and gustiness, with a joint analysis of SuperCam microphone data and MEDA wind, pressure, and temperature data for a comprehensive, multimodal, understanding of atmospheric dynamics [1].
Gaussian Process (GP) modeling will be extended to handle high-dimensional and time-frequency data, emphasizing kernel optimization and parameter tuning [4,5]. Multifidelity modeling approaches can be explored to combine simulations, and data sources [6]. The work also involves integrating wind models to validate surrogate models and refine turbulence characterization, developing time-frequency surrogate models that merge data-driven predictions with physical simulation outputs. Additionally, the internship will investigate the dissipation of Martian winds, characterizing fine-scale turbulence dynamics and identifying correlations between gustiness and environmental factors like pressure drops, temperature gradients, and energy fluxes. Broader applications include extending the developed methods to future planetary missions, terrestrial analog studies, climate modeling, and aerospace system optimization. Additionally, as many machine learning advances in GP modeling have been implemented in the open-source Surrogate Modeling Toolbox (SMT 2.0), part of the internship will involve the development of new tools and functionalities within this framework to support the project's objectives [7].

External/Internal references

1) Stott, A. E., Murdoch, N., Gillier, M., Banfield, D., Bertrand, T., Chide, B., De la Torre Juarez, M., Hueso, R., Lorenz, R., Martinez, G., & Munguira, A. (2023). Wind and turbulence observations with the Mars microphone on Perseverance. Journal of Geophysical Research: Planets, 128(5).
2) Roustant. O. (2024) Metamodeling with Gaussian processes. Lecture Notes and exercices. INSA, pp.55.
3) Banfield, D., Spiga, A., Newman, C., Forget, F., Lemmon, M., Lorenz, R., Murdoch, N., et al. (2020). The atmosphere of Mars as observed by InSight. Nature Geoscience, 13(3), 190–198.
4) Wilson, A., & Adams, R. (2013). Gaussian process kernels for pattern discovery and extrapolation. International Conference on Machine Learning.
5) Henderson, I., Noble, P., & Roustant, O. (2023). Covariance models and Gaussian process regression for the wave equation. Application to related inverse problems. Journal of Computational Physics, 494, 112519.
6) Arenzana, R. C., López-Lopera, A. F., Mouton, S., Bartoli, N., & Lefebvre, T. (2021). Multi-fidelity Gaussian process model for CFD and wind tunnel data fusion. Proceedings of AeroBest 2021.
7) Saves, P., Lafage, R., Bartoli, N., Diouane, Y., Bussemaker, J., Lefebvre, T., Hwang, J. T., Morlier, J., & Martins, J. R. R. A. (2024). SMT 2.0: A surrogate modeling toolbox with a focus on hierarchical and mixed variables Gaussian processes. Advances in Engineering Software, 188, 103571.