

Hybrid Approaches to Understand Martian Water-Ice Cloud Properties for Planetary Atmospheric Applications

C.L. Campbell (1), J.E. Moores (1), G. Benedix (2), S. Meka (3), A.L. Rohl (3), K. Chai (3), D. Marrable (3).

(1) Centre for Research in Earth and Space Science, York University, Toronto, ON M3H 1P3, Canada, (2) Space Science and Technology Centre, School of Earth and Planetary Sciences, Curtin University, Perth, WA, 6845, Australia. (3) Curtin Institute for Computation, Curtin University, Perth, WA, 6845, Australia. (ccamp93@yorku.ca)

Abstract

Machine learning (ML) with optical flow has been utilized to estimate cloud properties such as wind direction and optical depth above Gale crater on Mars as an analog for any planetary atmosphere with condensable clouds. The algorithm was tested on atmospheric movies taken by the Mars Science Laboratory (MSL) rover, also known as Curiosity, and the results are compared to manual calculations. Applications of this algorithm on future planetary spacecraft could significantly reduce downlink data volume by locally calculating parameters instead of transmitting multiple images back to Earth for manual analysis.

1. Introduction

Images of clouds acquired from the surfaces of other planets can help us better understand the workings of atmospheres, including the transfer of aerosols such as water and dust. Currently, we capture movies of clouds from the surface of Mars which amazes and inspires when shown to the public. No two movies are the same as the weather is ever changing, shedding light on a dynamic component of the Martian environment. However, acquiring cloud movies requires a great deal of data volume to be transferred back to Earth (order of 10 Mibits), hence these videos are acquired infrequently, typically once or twice a week. Once these images are downlinked, a human operator analyzes them.

The collaboration between Curtin University and York University has shown that hybrid approaches involving Computer Vision (CV) and ML based algorithms are able to extract key environmental parameters such as cloud direction, angular velocity, and optical depth. Were such an algorithm deployed on a future rover, a single movie would consume

significantly fewer resources, replacing the 10 Mibit observation with one that is only a few bytes.

2. The Significance of Clouds

Martian water-ice clouds have been studied from both Mars orbit [2, 5, 15] and surface [3, 6, 9, 10, 11, 12, 13, 16] to understand intrinsic properties of the Martian atmosphere. Every Mars Year (MY) from solar longitude (L_s) 45°–150°, when Mars is furthest from the sun and atmospheric temperatures are lower, the Aphelion Cloud Belt (ACB) forms in the equatorial region, offset towards the North [5]. This cloud belt highlights the results from Martian atmospheric models that revealed the formation of a single cross-equatorial Hadley cell [7]. Since this cell allows water to move from the north to south hemisphere [14], monitoring the strength and timing of ACB clouds provides information on the hemispheric transport of water on Mars.

3. Optical Flow and Machine Learning

Several CV based techniques such as optical flow [17] and particle image velocimetry [8] are used among others [4] to estimate the velocity field of moving objects. When used in isolation and for images with high signal-noise-ratio, pure CV based workflows prove to be resilient in cases where there is little distortion in features of interest between successive image frames. Martian cloud movies, on the other hand, contain cloud patterns that change shape, gyrate, and may be subject to aliasing errors when processed and transmitted back to Earth. To circumvent these issues, a two-stage hybrid approach is proposed. Optical flow is first used to generate directional vectors and local velocities; secondly ML is applied to smooth the CV generated data to correct for erroneous vectors. In this implementation, random noise of varying intensity is added to several image sequences,

generated from random image sets of clouds, streets, and buildings. These synthetic images are randomly generated with a predetermined traverse width. An ML model is trained to predict the known values of the relative velocity and slope from a list of directional vectors generated using optical flow. Since the features in the image are not directly propagated into the network, the prediction is immune to the specificity of the image; hence the model is trained on synthetic images then tested with Martian atmospheric movies.

4. Methods: Testing with the Curiosity Cloud Movies

Currently, Curiosity captures atmospheric movies to monitor cloud activity, especially during the ACB season. The navigation cameras take two types of movies: supra-horizon (SHM) and zenith (ZM). The only difference between the two is the elevation. A SHM is pointed just above the crater rim and a ZM is pointed directly above the rover towards the zenith point. Atmospheric movies are acquired every 2-3 sols (Martian day) and are approximately 225 seconds long. These observations have been used to estimate several cloud parameters such as optical depth [9] and altitude [3]. Using both atmospheric movies, [9] found the average optical depth of clouds to be 0.02 on average, indicating thin clouds. [3] compared observed wind parameters in ZMs to an atmospheric model to estimate altitude. The vertical pointing of a ZM allows cloud features to be followed manually to determine wind direction and angular distance. Employing a computational technique to track the cloud features will aid in analyzing parameters that are currently done manually.

5. Results and Discussion

A machine learning algorithm was developed at Curtin University to aid in calculating cloud parameters. Several examples of ZMs of varying quality types were provided for testing while known data was used to train the algorithm. For sol 1957 the meteorological wind direction was manually calculated as 235° , which is consistent with computation results depicted by a red arrow in Fig. 1.

Future work will focus on automatic extraction of other important parameters such as angular wind velocity and opacity (based on defining the areas of the brightest and dimmest value).

The development of onboard pre-processing algorithms will benefit future planetary missions by downlinking direct cloud parameters rather than a string of images that have higher data volume.

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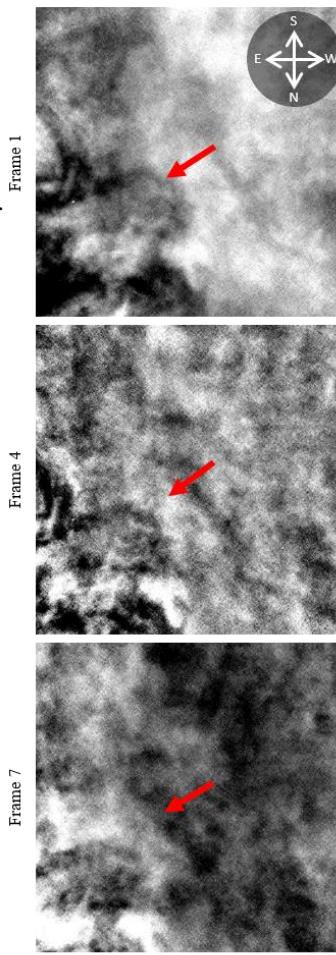


Fig. 1: Sol 1957 ZM (07:40 LTST, L_s 126°). Frames are processed with the mean frame subtraction technique to enhance faint clouds. A compass in the top-right corner shows North relative to the frames. The red arrow represents meteorological wind direction.