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Automated Image Interpretation for Science Autonomy in Robotic Planetary Exploration

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Graduate Program in Electrical and Computer Engineering

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AUTOMATED IMAGE INTERPRETATION FOR SCIENCE AUTONOMY IN ROBOTIC PLANETARY EXPLORATION (Thesis format: Integrated Article)

by

Raymond Francis

Graduate Program in Electrical and Computer Engineering

A thesis submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy

The School of Graduate and Postdoctoral Studies The University of Western Ontario London, Ontario, Canada

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Abstract

Advances in the capabilities of robotic planetary exploration missions have increased the wealth of scientific data they produce, presenting challenges for mission science and operations imposed by the limits of interplanetary radio communications. These data budget pressures can be relieved by increased robotic autonomy, both for onboard operations tasks and for decision-making in response to science data.

This thesis presents new techniques in automated image interpretation for natural scenes of relevance to planetary science and exploration, and elaborates autonomy scenarios under which they could be used to extend the reach and performance of exploration missions on planetary surfaces.

Two computer vision techniques are presented. The first is an algorithm for autonomous classification and segmentation of geological scenes, allowing a photograph of a rock outcrop to be automatically divided into regions by rock type. This important task, currently performed by specialists on Earth, is a prerequisite to decisions about instrument pointing, data triage, and event-driven operations. The approach uses a novel technique to seek distinct visual regions in outcrop photographs. It first generates a feature space by extracting multiple types of visual information from the image. Then, in a training step using labeled exemplar scenes, it applies Mahalanobis distance metric learning (in particular, Multiclass Linear Discriminant Analysis) to discover the linear transformation of the feature space which best separates the geological classes. With the learned representation applied, a vector clustering technique is then used to segment new scenes.

The second technique interrogates sequences of images of the sky to extract, from the motion of clouds, the wind vector at the condensation level — a measurement not normally available for Mars. To account for the deformation of clouds and the ephemerality of their fine-scale features, a template-matching technique (normalized cross-correlation) is used to mutually register images and compute the clouds' motion.

Both techniques are tested successfully on imagery from a variety of relevant analogue environments on Earth, and on data returned from missions to the planet Mars. For both, scenarios are elaborated for their use in autonomous science data interpretation, and to thereby automate certain steps in the process of robotic exploration.

Keywords: robotic autonomy, planetary exploration, computer vision, natural scene interpretation, distance metric learning, machine learning, Mahalanobis distance, Linear Discriminant Analysis, image registration, normalized cross-correlation, planetary science, geology, atmospheric science

Co-authorship statement

Chapters 3 through 6 represent technical papers prepared for other fora before their integration here to describe the present research program. Each has several co-authors, a testament to the collaborative and interdisciplinary nature of the research.

Kenneth McIsaac, co-author on chapters 3 - 6, is the student's primary research supervisor in the graduate program in Electrical and Computer Engineering. He provided guidance throughout the research program, including in the selection and formulation of the problems, and selection and evaluation of techniques to address them. He also provided support in the presentation of the work in each forum, especially for chapter 5.

Gordon R. Osinski, co-author on chapters 3-6, is the student's co-supervisor, providing guidance especially in planetary geology. He provided insight and instruction in the practice of terrestrial and planetary field geology, including an understanding of the types of problems to be solved and the operational implications of tools to address them. He led, or supervised, most of the field expeditions on which data was gathered for each investigation reported here.

John Moores, co-author on chapters 5 and 6, is the student's supervisor in the Mars Science Laboratory (MSL) mission science team, and became an academic co-supervisor during the research program. He originated the technique of manual cloud-tracking for wind estimation on the Mars Phoenix mission, and proposed the project to automate it. He provided access to the MSL mission, allowing new data to be gathered and the automation work to be funded.

David R. Thompson, co-author on chapters 3 and 4, hosted and supervised the student as a Visiting Student Researcher at the NASA Jet Propulsion Laboratory, California Institute of Technology. He provided guidance in machine learning techniques and interpretation of natural scenes in the context of exploration, and led a field expedition on which much of the data for the geologically-focused investigation was gathered.

Claire Newman, co-author on chapter 6, is a colleague on the MSL science team and a specialist in climate modeling and atmospheric science. She provided the data from her work with the MarsWRF model to support interpretations and conclustions drawn from the MSL wind observations presented in chapter 6. This included preparing Figure 6.4.

David Choi, co-author on chapter 5, was consulted on past experience in techniques for feature-based tracking of clouds in the atmosphere of Jupiter.

Epigraph

Moreover, there is an infinite number of worlds, some like this world, others unlike it. . . . And further, we must not suppose that the worlds have necessarily one and the same shape. For nobody can prove that in one sort of world there might not be contained, whereas in another sort of world there could not possibly be, the seeds out of which animals and plants arise and all the rest of the things we see. . .

Further, we must hold that to arrive at accurate knowledge of the cause of things of most moment is the business of natural science, and that happiness depends on this (viz. on the knowledge of celestial and atmospheric phenomena), and upon knowing what the heavenly bodies really are, and any kindred facts contributing to exact knowledge in this respect.

Epicurus, Letter to Herodotus, circa 300 BCE

Acknowledgments

This thesis is the product of a complex, interdisciplinary, and very busy research program which would not have been possible without the support of a large number of people. On reflection, the number of rich experiences, enabled by great teams of people, that I've been able to take part in during this degree program is remarkable, and I'm very thankful.

Dr. Ken McIsaac has provided throrough, helpful, and close support and guidance throughout the research program. He has consistently made time to consult on this work, despite his numerous other responsibilities. His guidance has consistently been helpful, timely, and respectful, and has allowed a level of close co-operation that greatly enhanced both the work and my experience as a graduate student. His willingness to support a complex and ambitious research program with numerous collaborators and complementary elements enabled the success of this research, and allowed me to gain experience and knowledge I could not otherwise have had.

Dr. Gordon Osinski provided an essential element to this program – close consultation and support from an experienced expert in planetary geology. His active field program afforded me experiences far beyond what is normally available to a student of Electrical and Computer Engineering. He assigned me to rare and valued slots on field expeditions to remote arctic research sites, and trusted me with important roles in his analogue mission research project. From these I gained the underestanding of field geology, and of mission operations to support it, that I needed to formulate and pursue this research program.

Dr. John Moores brought an unexpected and unparalleled opportunity in his offer to participate in a proposal to the Mars Science Laboratory Participating Scientist program. Supporting MSL, both in developing the automated data interpretation tools, and in learning to work in mission operations for a rover on the surface of Mars has been an exciting, humbling, and fulfilling experience. It has greatly enhanced this research program — I can't think of a better activity to enrich a degree in robotics, or to demonstrate the value of engineers understanding well the science served by the tools they build.

Along with John, several members of the MSL science team have been very helpful in preparing the observation campaign reported in this thesis, and in guiding me through my training in mission operations. These include Keri Bean, Mark Lemmon, Claire Newman, Michael Mischna, Manuel de la Torre Juarez, Michael Wong, Tim McConnochie, Amy Culver, and Roger Wiens.

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TextureCam research team, and the Mojave desert field tests were all great chances to learn from helpful, capable colleagues. Some of those include Dmitriy Bekker, Kiri Wagstaff, Brian Bue, and Bill Abbey.

Here at Western, the Centre for Planetary Science and Exploration (CPSX) provided another fertile environment for learning what I needed to complete this work. The ability to follow nearly all elements of the planetary science graduate program, in addition to the full program in engineering, was a rare opportunity that paid back well for the extra effort it demanded. Immersion in a large and active group conducting research on nearly every aspect of planetary exploration provided no shortage of new knowledge and camaraderie, and filled in the context for my own efforts to contribute to the field.

Much of what I learned came from working closely with a number of colleagues, especially Dr. Osinski's students, on field expeditions. Particular thanks for helping my field studies go to Cassandra Marion-Beauchamp, Marc Beauchamp, Annemarie Pickersgill, and Marianne Mader, along with Tim Barfoot and Braden Stenning of the University of Toronto Institute for Aerospace Studies, Anthony Jenkinson of the Innu Nation, and the anonymous employee of Innu Mikun Airlines who made sure their Twin Otter had an emergency survival kit.

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The implementation of Linear Discriminant Analysis makes use of the Matlab Toolbox for Dimensionality Reduction v0.8.1, produced and distributed by Laurens van der Maaten of the Technische Universiteit Delft.

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List of Abbreviations

AEGIS	Autonomous Exploration for Gathering Increased Science
ANN	artificial neural network
APXS	Alpha Particle X-ray Spectrometer
ARI	Adjusted Rand Index
CSA	Canadian Space Agency
DRT	Dust Removal Tool
ECMWF	European Centre for Medium-Range Weather Forecasts
EM	electromagnetic
ESA	European Space Agency
EU	European Union
EUMETSA	T European Organisation for the Exploitation of Meteorological Satellites
FP5	Fifth Framework Programme
GCM	general circulation model
GMS	Geostationary Meteorological Satellite
GOES	Geostationary Operational Environment Satellite
Hirise	High Resolution Imaging Science Experiment
HSV	hue-saturation-value
IEEE	Institute of Electrical and Electronics Engineers
IR	infrared
i-SAIRAS	International Symposium on Artificial Intelligence, Robotics and Automation in Space

ISPRS International Society for Photogrammetry and Remote Sensing

- JPL Jet Propulsion Laboratory
- LDA Linear Discriminant Analysis
- MAHLI Mars Hand Lens Imager
- MDA Multiclass Discriminant Analysis
- **MDA**^{*} MacDonald, Dettwiler and Associates
- MER Mars Exploration Rovers
- MR8 Maximum Response 8 (filter bank)
- MRO Mars Reconnaissance Orbiter
- MSL Mars Science Laboratory
- **mSM** Mobile Scene Modeler
- **MSSS** Malin Space Science Systems
- **NASA** National Aeronautics and Space Administration
- NCA Neighbourhood Components Analysis
- **NESDIS** National Environmental Satellite Data and Information Service
- **NMR** nuclear magnetic resonance
- **NSERC** Natural Sciences and Engineering Research Council of Canada
- **OASIS** Onboard Autonomous Science Investigation System
- **OCPP** Orbiter Cloud Photopolarimeter
- **PCA** principal components analysis
- **PET** positron emission tomography
- **RANSAC** Random Sample Consensus
- **REMS** Rover Environmental Monitoring Station
- **RGB** red-green-blue
- SIFT Scale-Invariant Feature Transform
- **SLAM** simultaneous localization and mapping
- **SLR** single lens reflex
- **SSI** Surface Stereo Imager

SURF	Speeded Up Robust Features
TLS	terrestrial laser scanner
TRL	Technology Readiness Level
US	ultrasound
UV	ultraviolet
VIRTIS	Visible and Infrared Thermal Imaging Spectrometer
WMO	World Meteorological Organization
XRT	x-ray tomography

Chapter 1 Introduction, Context, and Motivation

The first decade of the twenty-first century has seen an unprecedented period of progress in the robotic exploration of the solar system. At present, spacecraft missions are underway to the Earth's moon, all but the outermost planets, and several minor bodies across all regions of the system. The missions have produced tremendous amounts of data from the instruments they carry, allowing new discoveries that have greatly affected our understanding of the Earth's neighbourhood. This large data volume presents challenges for mission scientists and engineers, however, as radio links over interplanetary distances limit the rate at which the data can be returned to Earth. In fact, the bottleneck of the communications system is a key driver for the entire mission architecture used in planetary missions, from the selection of instruments and design of spacecraft subsystems to the scheduling of observations and the choice of landing sites and targets of investigation.

Even after the data is delivered to Earth, significant challenges remain in making the best use of it. A single mission can gather data for many years, and several missions to the same or similar target bodies can produce great volumes of data that are difficult to analyze as a whole. Significant effort is needed, and not always available, to thoroughly investigate incoming data, and new discoveries are often found by reviewing old data and comparing it with newer acquisitions.

New data processing techniques can present a way of addressing both problems – data reduction aboard the spacecraft and interpretation on Earth. For data from imaging systems, this can take the form of autonomous image-processing techniques, which allow computer systems to autonomously identify features of interest in images. A great variety of such techniques have been developed to address specific problems in terrestrial applications, but the application of autonomous image-processing to the types of problems found in planetary exploration remains very new, with a great many potential uses.

The present work develops new approaches to autonomous robotic science in the context of planetary exploration. It begins by assessing current challenges in planetary science to find promising areas for science autonomy focused on image processing. It then addresses specific problems of image processing of natural scenes in geology and atmospheric science, producing new techniques to automatically extract semantically-useful data from photographs. These techniques are tested on imagery of representative scenes from a variety of relevant terrestrial analogue settings, as well as on data from surface missions to the planet Mars. Finally, scenarios are presented to incoporate these new tools into autonomous robotic science operations in planetary missions, respecting the typical constraints of mission design and operation, and the practice and goals of robotic field science as practiced in surface missions.

1.1 Context: Planetary exploration

1.1.1 Planetary science

Speculation about the nature of other worlds has been common since antiquity [1], but only since the invention of the telescope could these discussions be informed by observational data [2]. Continued advancement in imaging techniques has allowed new insights into the nature of the planets, often with revolutionary implications for our understanding of the Earth and its place in the universe. Knowledge gained from the use of ground-based telescopes has been expanded as spacecraft took images from progressively closer vantage points, first flying by, then orbiting, then landing on other worlds.

With time, the modern understanding of the solar system emerged. The planets and minor

bodies which inhabit the solar system are now known to have formed from a common protosolar nebula [3]. During their formation and evolution, common processes affected them all, bringing each to the state in which we find it today. The modern, interdisciplinary practice of planetary science is to consider each of these bodies as discrete examples from a continuous spectrum of variation in the way planets can form, given the materials from which they are derived, their size, their position relative to the parent star, and other key variables. The recent discovery of large numbers of exoplanets has helped to solidify this view, and to shed light on the space of variation for the planet-forming process [4].

In modern planetary science, then, processes which are common to several planetary bodies can be best studied by comparison of examples across locales. Impact cratering, for example, long thought to be absent or nearly so on Earth, is now seen as a dominant process on the surface of planetary bodies having a solid surface [5]. Models of impact crater formation are now discussed in the context of examples from all the terrestrial planets, as well as satellites and minor bodies throughout the solar system. Impact craters on Earth are used as test cases for the models, and as ground truth for the assumptions on which they are based, being much more accessible than craters on other bodies. Terrestrial craters are also used as analogues for the geology and terrain to be found on the Earth's moon, on Mars, or on other worlds, given the prevalence of craters as a landform on those bodies. Studies of atmospheres, volcanism, erosional processes, and planetary interiors are all conducted in this powerful context of each planet as a particular case of a general phenomenon.

Working in that context requires the use of datasets from the planetary bodies to be explored, all obtained by instruments aboard spacecraft sent to explore the solar system. A great many techniques are now available, using magnetism, radar, laser altimetry, studies of the variations in radio signals from spacecraft, and more, but imaging in the visible and adjacent bands remains a key technique. Landforms are identified and interpreted from orbital imagery, and regional and global maps are built up [6]. Images from landed platforms stand in for the eyes of geologists, acting as an initial and primary reference for the environment surrounding the lander. The practice over many years has been for images to be sent to Earth for study, and based on the interpretations of these images by geologists, for further imagery to be taken of particular targets, in a process which becomes cyclical.

These images, primarily visible-wavelength photographs, are the key tools for navigation of mobile assets on planetary surfaces. Rovers are guided towards targets of interest identified by scientific interpretation of received imagery. Safe routes towards the targets, obstacles, and dangerous terrain are identified by an engineering analysis. This again requires a cyclical process in which images are captured and sent to Earth for interpretation, then decisions based on their interpretation are formulated into commands for rover motion and new imaging. The operational and scientific use of the imagery happen side by side, and are dependent on each other, forming a fundamental working process of planetary mission operations.

1.2 The challenge of communications

Data from spacecraft throughout the solar system is sent back to Earth by a remote communications link, with radio-frequency links still the best available. These spacecraft operate at great distances from their ground stations – even the closest planets are tens of millions of kilometres away from the Earth. This, along with the limited size of antennas and power available for transmission, and other operational restrictions, limits the rate at which data can be sent over the communications links.

This data limitation is a key restriction on the capabilities of a planetary mission, and drives the design of the mission architecture, the operations planning, and the selection of instruments. Instrumentation and experiments which produce high volumes of data compete for the limited data budget, and may not be worth including if they can be used only infrequently. Very high resolution imagery is often very desirable for the level of detail visible in observed features, but when digital images are large, fewer of them can be transmitted. Data-heavy operations may need to be scheduled to use separate communication cycles, complicating mission planning and reducing the versatility of the overall spacecraft system. And the need for a fraction of the data to directly support engineering and planning needs means that the budget for science data is even further constrained.

In many cases a mission could be much more capable if its communications limits could be relaxed – if the instrument data products were smaller, the data budget larger, or the amount of data needed to answer a question or make a discovery lower. Reducing the number of observations to fit the data budget decreases the effective scope of the mission. But a second problem also throttles the rate at which the mission can work. This is the need to send imagery to Earth for intepretation.

Regardless of scale or type, the features captured in planetary imagery must be interpreted by human operators, all of whom, at present, work on Earth. This step requires:

- the transmission of the data to Earth,
- dissemination of data to the science team,
- time for interpretation of the imagery and comparison with other data,
- decision-making with respect to next steps for the mission, given the new data, and
- preparation of the next cycle's commands and their upload to the spacecraft

The interpretation of the data and the steps taken to enable it take time, and introduce a necessary cadence of data-interpretation and command cycles into the mission operations. Since the spacecraft often cannot continue work until new commands are sent to it on each cycle, the time taken for data interpretation on Earth limits the rate at which mission objectives can be carried out. Faster interpretation of data, or a reduced need to have humans perform the interpretation, would in some cases improve mission performance.

1.3 Addressing the problem: autonomous science

To address the challenges of transmitting and interpreting planetary imagery, a possible strategy is to improve the ability of computer systems to autonomously interpret image data. Increased autonomy of instruments could mean that short statements of the interpretation could be sent to Earth instead of large sets of images, at a reduced data cost, freeing up space in the data budget for other observations. Overall, more scientific work could be accomplished for the same data budget, even if fewer images are returned to Earth. Initial progress has already been made in this area, with the Mars Exploration Rovers (MER) able to select rocks of scientific interest based on albedo [7] and automatic detection of certain transient surface events aboard the Earth Observing One satellite [8].

Even for image sets sent for human analysis, automated or computer-aided interpretation could speed the work of science teams, guiding them to key features or unexpected observations. In some cases the gain will be in reliability – humans will make mistakes and oversights, but the computer can provide a redundant mode of image inspection, possibly seeing things that humans overlook. In other cases the gain will be from efficiency – the time spent interpreting a large series of images can be used for other work if the interpretation can be reliably performed by computer. Even if the computer can provide a first-order interpretation, selecting key targets or classifying features before they are presented to scientists, significant savings may be possible. Finally, gains may be found in the correlation of data from long data series, or across data series in the comparison of data from multiple sensors. Autonomous image processing could prove a very valuable tool for spacecraft science teams, even if it is used on Earth, rather than aboard the spacecraft.

1.4 Research problem

The autonomous interpretation of planetary image scenes represents a broad class of image processing problems. They are unified by the common task of detecting, classifying, and iden-

tifying features of interest in natural scenes of planetary surfaces and atmospheres at a range of scales. They have the common motivation of enhancing the performance of planetary exploration missions by reducing the data volumes needed for specific observations, and the task load of scientists analyzing and interpreting data. They have a common target user and principal beneficiary: the planetary scientist, whose work of analyzing data of many types and sources would benefit from more powerful analytical tools.

Within this set of problems, a variety of specific tasks exist, each best suited to particular image-processing algorithms and techniques. In all cases, however, the common goal of improving autonomous robotic science leads to a consistent approach. The image-processing technique developed must automate a task of image interpretation which currently requires a ground-in-the-loop control cycle for planetary missions. To be useful, it must solve a genuine problem of extracting useful information from images of natural scenes, representative of the kinds of scenes to be interpreted in real mission settings. To be of practical value to future science missions, it must moreover address this problem in a way that produces meaningful science information relevant to the stepwise processes used to understand and explore a region of a planet's surface.

For missions operating on planetary surfaces, two broad domains of such problems present themselves: studies of the planet's surface, and studies of its atmosphere. For surface investigations, geology is a prime focus, with an essential task being the recognition, classification, and mapping of different types of surface materials. This information underpins every higherlevel interpretation of the nature and history of a geological setting, and guides geochemical and mineralogical studies using non-photographic instruments. For the atmosphere, a main image-interpretation task is the detection and tracking of transient visible features, such as clouds, whose form and motion reveal much about the physical conditions and dynamics of the atmosphere.

The present work addresses problems representative of the kinds of computer vision tasks needed for science autonomy in each domain. For geology, a new technique is developed to automatically segment photographs of rock outcrops by rock type, with numerous potential applications to mapping, guiding autonomous instrument targeting, target selection, and data triage. For atmospheric science, a new technique is developed to track clouds in sequences of photographs of the sky, with application to studies of winds aloft and the dynamics of the atmosphere far above sensors on the planetary surface.

1.4.1 Segmentation of images of rock outcrops by geological unit

Visible-wavelength cameras are universally included on landed platforms, as they provide a wealth of information readily understood to humans viewing their imagery. They are also a standard tool of field geologists, who use them to record their observations for later analysis and review. A wealth of images of geological scenes exists both for sites on Earth and other planets.

A key task for human geologists studying rock outcrops (in photographs, or in person) is to recognize the boundaries between different and adjacent types of rock. Detecting the spatial distribution of such variations in material is the first step towards understanding the spatial relationships between different materials, and identifying the materials themselves — and thus to all of the study and interpretation undertaken of a geological setting.

The potential scientific value of autonomous geological classification is considerable. As an example application, impact craters are a dominant geological process on all planetary bodies with solid surfaces [9]. Identifying the position and relationships between emplacements of impact-generated materials is a central task of understanding the formation and nature of an impact crater [5]. Discovering and interpreting these relationships requires the identification and classification of the geological units which can be seen, for example as impact melt rocks (derived from material melted and re-solidified during the impact), impact breccias (formed by fragmentation, mixing, and re-lithification of rocky materials during the impact), and target rocks (the original materials present at the site prior to the impact event) [10]. An understanding of the history of the impact structure and the impact process itself depends on correctly interpreting the arrangements of these materials – which occur together and separately, which types overlie others, and such.

But more generally, such techniques of identifying rock types within a scene ('geological units') and the relationships between them, is a core technique of geological exploration [11]. The techniques used for classification and segmentation of geological scenes would likely see application, adapted for each case, to a great variety of environments both on Earth and throughout the solar system. An autonomous geological classifier, even one which works only for specific rock types or specific environments, would be a very valuable tool for increasing the autonomy, scientific return, and scientific discovery rate of planetary exploraton missions.

The current state of literature with respect to automated image interpretation for geology, science autonomy in planetry exploration, and relevant image-processing and data analysis techniques is given in section 2.2 and its subsections.

1.4.2 Cloud-tracking for winds-aloft studies on Mars

The goal of this investigation is to demonstrate autonomous estimation of the wind direction using images of the Martian atmosphere taken from a landed platform. The task requires an image-processing algorithm working on a series of images of the same part of the Martian sky taken over a short period of time. The algorithm would identify clouds, track them as they move in the camera's field of view over the course of the image series, and, with knowledge of the camera pointing and relevant geometry, determine the wind direction.

Such an algorithm would reduce a large set of image data to a single short string of digits describing the wind direction, at significant data savings should it later be implemented on a spacecraft. For Earthbound use, it would greatly improve the speed at which cloud-based wind studies could be conducted, allowing the study of large, long-term datasets quickly. A study of such image sets allows investigation of wind at altitude on any planetary surface mission where a suitable camera is present (rather than requiring specialized atmospheric sounding systems rarely available on spacecraft), greatly increasing the potential for martian atmosphere studies

both on future missions, and using archived data. A consequence of such studies would be a source of new, previously unavailable reference data for ground-truthing (so to speak) numeric circulation models of the Martian atmosphere.

Such a tool would allow a greater understanding the wind patterns in the condensing (i.e., cloud-forming) layers of Mars' atmosphere both diurnally and over the course of years, an analysis which would be very difficult and labour-intensive to do manually. This investigation has implications for heat, mass, and water transport in the Martian atmosphere, and thus for planetary climate modeling. The wind patterns also have implications for the transportation and preservation of fine geological materials – clay, dust, sand, and others – that can include biomarkers, the evidence for past biological activity. Unknown behaviour of wind in the Martian atmosphere is also a major source of uncertainty for spacecraft entering and descending through the atmosphere to land, and the models used in designing these systems would benefit from a greater understanding of the atmosphere's behaviour.

The history and current state of research of cloud-tracking in computer vision and in planetary science, along with relevant image processing techniques, are described in section 2.3 and its subsections.

1.5 Research contributions

The work described in the subsequent chapters details several related research contributions. In particular, these include:

- A novel technique for processing a photograph of a geological scene to generate a feature space of visual characteristics which contains information relevant to the task of discriminating between types of rock.
- A new technique for autonomous segmentation of geological images using only colour photographs, by searching for regions which are internally visually similar, while being mutually distinct from each other. This technique has been demonstrated successfully in

a number of visually-challenging geological scenes of relevance to planetary exploration. These include images from several planetary analogue sites on Earth, and high-value science investigation sites visited by the Mars Science Laboratory (MSL) mission on Mars.

- A strategy for employing autonomous geological image segmentation to enable greater science autonomy in robotic planetary surface missions, including a formalization of the process of robotic geological exploration compatible with the practices of both field geology and planetary robotics. The elaborated scenarios include several scales of implementation for a variety of tasks, encompassing the space of instrument suites and science investigations foreseen for planetary missions over the coming decade and beyond.
- A novel technique for autonomously processing sequences of images of clouds as viewed from below, to compute the wind vector at the cloud altitude by application of image cross-correlation. This technique has been demonstrated successfully on images of a variety of cloud morphologies from Earth and the Mars Phoenix mission, and is now in routine use to support data processing from the MSL mission.
- The first comparative analysis of winds observed at the surface and aloft, at equatorial latitudes on the planet Mars, using data from the MSL mission.
- A strategy for onboard autonomy to conduct monitoring on Mars of a previously unavailable meteorological variable — the condensation-level winds — at efficient data cost, by using automated image analysis. This includes an assessment of the requirements for such a system, and the decision case for implementing it.

In addition, the techniques developed during the research program leading to the above contributions were also used to enable additional research not presented in this document. These include, especially, contributions to the evaluation and field testing of a system of geological surface classification [12], and the development of a novel architecture for mission science operations during robotic exploration [13], [14].

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Chapter 2

Literature Review and Background

2.1 Image processing for classification

The task of image segmentation and classification is a classic problem of machine vision. Numerous basic image characteristics can be used to discriminate between regions in an image. Colour, intensity, and the numerical derivatives thereof can be assumed to correlate to the presence of particular objects, materials, or features. Edge-detectors and contour techniques can exploit these characteristics to find boundaries, with suitable assumptions and parameters. More advanced mathematical techniques – Gabor filters, wavelet and Fourier transforms, or component analyses, for example – can be applied in an effort to extract less immediatelyapparent information from the pixels. These are particularly useful where experience or an understanding of the mechanisms underlying the formation of the viewed scene give an insight into their relation to the appearance of the objects viewed. This often applies to visual texture, where the statistical patterns of image pixels can have, at once, a mathematical distinctness, a correlation to a real object or feature, and a distinct visual appearance, for given image regions.

2.1.1 Natural scenes

Natural scenes present a particular challenge for segmentation. Such scenes are often complex, with many types of textures in a single scene, and texture regions having irregular, poorly-defined, or gradational boundaries. There are often complex relationships between the basic

image characteristics for given regions, and signifiant variation in the properties of a given object or feature can exist. Multiple signals can overlay each other, and noise or unrelated processes can overlay or partially obscure the features of interest.

Such is the case in geology. Rocks are often very complex in appearance, and a field geologist requires a great deal of training and experience to be able to identify rocks visually [1]. Even then, full classification of rocks must often wait for detailed microscopic or chemical investigation, due to the fine scale of key features, or ambiguity due to the similar appearance of different rock types under varying conditions, such as weathering. Basic heuristics and selective inspection techniques are taught to new geologists in field courses, where students see rocks of various types in their natural settings, and learn to discriminate between them and map their extent and relationships [2]. Such knowledge is gained alongside theoretical courses in the chemistry and physics that drive the formation, morphology, and appearance of rocks. The two can be correlated, to an extent, and an analytical understanding of the expected appearance of geological materials can help in their classification, but the visual mechanics are not always conscious. Much depends on the experience, keen eye, and familiarity of the geologist with the materials at hand.

2.1.2 Complex and variable natural scenes: the example of medical imaging

Heuristics and the familiarity of experts had long been the basis for interpreting medical images as well. These, like planetary images, display complex natural scenes, prone to noise, acquisition limitations, and significant variability in the appearance of features. Unlike for planetary imagery, much work has been done in the field of automated processing of medical images, driven by the much wider use of medical imaging, the significant costs associated with assigning physicians and radiologists to visually interpret images, and the potential for human error. Decades of research have led to very succesful automated interpretation algorithms for autonomous segmentation and classification of complex images with noise, poorly-defined boundaries between regions, and other challenges to automated interpretation. Planetary scenes have been much less studied for the purposes of automated interpretation, but their interpretation faces many of the same difficulties, and techniques which have shown success in medical imaging may well provide guidance to the interpretation of geological and atmospheric scenes.

Medical images concern the interior of the human body, which presents a complex collection of tissues having variable appearance and irregular boundaries. Regardless of the modality used – x-ray tomography (XRT), nuclear magnetic resonance (NMR), positron emission tomography (PET), or other – the problem is usually one of segmentation and classification, with the goal of identifying tissues to find tumours, inflammation, or tissue features indicating trauma or disease. Such an effort represents the segmentation and classification of natural scenes having a highly complex and variable appearance and very large parameter space [3]. As in imagery of geological scenes, medical images are also affected by variations in acquisition, leading to differences in speckle, contrast, brightness, and missing boundaries [4]. In geological imagery, similar difficulties are presented by changes in lighting, weathering and dust covering on rocks, vegetation (on Earth), and instrument differences.

Meeting or mitigating these challenges to achieve useful automated image processing is a difficult task. In the medical field, ultrasound (US) is a particularly challenging modality, due to the high incidence of speckle, poor signal-to-noise ratio, low contrast resolution, and frequent discontinuity of boundaries [5]. Patient motion during imaging adds to the difficulty in localizing boundaries [6], and is nearly inevitable in imaging of cardiac, pulmonary, and other tissues. Such challenges have made direct analytical image analysis techniques difficult, and led to the use of statistical and pattern-recognition techniques in US image processing, of which [7] give a comprehensive review.

The challenges are similar to those for planetary scenes, where contrast and noise are limited by lighting conditions that cannot be controlled, and where boundaries can be obscured for a variety of reasons. Contacts – the boundaries between geological units – are often gradational, rather than sharp. Processes in impact crater formation and elsewhere can cause brecciation – fragmentation, mixing, and re-lithification of materials – leading to fragmentary and broken boundaries between rock types, while the edges of pre-existing geological units can be modified by the heat and pressure of new molten materials solidifying adjacent to them. Surface weathering, the overlay of dust, and erosion of the rock surface contribute to the noise in the image – such effects reduce the strength of the visual signal corresponsing to the rock itself, mixing it with other components. Atmospheric imaging faces similar problems, particularly in the dusty atmosphere of Mars, where the dust contributes to obscuration and effective noise, and where the clouds are of poorly-predictable, inconsistent, and dynamic morphology. Here, segmentation of individual clouds from the dust and the background sky, and classification of cloud types, will face similar challenges of noise, contrast, variability of appearance, and boundary ambiguity in geological and US imagery.

A great variety of techniques have been used for segmenting US images. Artificial neural networks (ANN) are very common, performing well at segmenting images of a variety of tissues, including in the heart [8], prostate [9], bloodstream [10], brain stem [11], liver [12] and elsewhere. Techniques using shape, physical, and other priors have also met with success, and may in some cases have analogies in geology. Knowledge about the expected clast shape in sedimentary rocks or breccias, or about the orientation of sedimentary beds, for example, could be used as prior information to inform a classification algorithm dealing with these kinds of materials. Similarly, models of cloud type and convective dynamics inform classification algorithms for atmospheric features. Energy-minimization methods are also used in US image analysis, as are Bayesian, level set, and active contour techniques, with [7] giving a comprehensive overview of the application of each.

Given the difficulties in managing the complex feature space of geological scenes, and the difficulty in reverse-engineering the visual heuristics of an experienced field geologist, such techniques may find similar utility in geological image interpretation as well, or, indeed, in many types of scenes to be found in planetary exploration applications.

2.2 Geological classification

Field geologists have traditionally used classical tools of exploration, such as the map, compass, hammer, and measuring tools [13]. Photographs are often taken of features of interest, and other imaging modalities such as lidar have come to be used in recent years [14], but such images are generally used as records, for reporting and later review. Attempts at providing automated interpretation of geological scenes have largely been driven by work in remote environments, including meteorite searches in Antarctica [15], and surface exploration of Mars [16]. For conventional geologists, image interpretation appears, to date, to remain largely the work of humans; one modern textbook on visual interpretation of geological scenes makes no mention of automated techniques [17]. The section that follows describes the current state of work in obtaining geological information autonomously by processing of photographic imagery.

2.2.1 Image-processing for geology

Geologists on Earth make use of direct visual inspection of rock features to interpret and understand the geology of a site. On Mars, or elsewhere in the solar system, this has not been possible, and all investigations are at present carried out with imagery and instrument data returned by robotic probes. In recent years, the data-collecting ability of these probes has increased, while data delivery to Earth remains restricted by the limitations of radio communication across interplanetary distances. This has led to research in onboard science data interpretation for both orbiting and surface probes, and relatedly, in techniques for autonomous decision-making and planning by the spacecraft in response to these interpretations.

As early as 1999, terrestrial analogue work included tests of on-board geological analysis. The Marsokhod deployment of that year [18] included tests of image-processing algorithms to detect rocks strewn on the ground surface, to find the horizon, and to detect layered structures in rock surfaces [19]. This layer detector gave inconclusive results, partly due to inadequate data acquired during the field test.

The rock detector in that test used the known position of the sun to derive expected positions of rocks by searching for shadows in images. It also had some difficulty, but was followed in subsequent years by other efforts with similar goals, though often different approaches. Castaño *et al.*[20], for example, developed a system using edge-detection in grayscale images. A system by Viola and Jones [21] used image integration and a cascade of different classification techniques applied to successively smaller and more confidently-selected image regions. Gor *et al.* [22] used pixel brightness and stereo range information. Thompson and Castaño [23] carried out a performance comparison of seven such systems, reporting on the merits of each. No detector was able to find more than 60% of the rocks in the test images, and the authors suggested that further research, or an alternate approach using non-visual sensors or sensor fusion, might give better results.

Nonetheless work has continued in using rock-detection systems to inform on-board decisionmaking. The Onboard Autonomous Science Investigation System (OASIS) algorithm, developed at NASA's Jet Propulsion Laboratory, used rock-detection and characterization to prioritize imagery for transmission [24], and led to the Autonomous Exploration for Gathering Increased Science (AEGIS) system used on the MER Opportunity rover [25], which is able to flag rocks for rover instrument work based on albedo. The OASIS system was further refined to use a broader set of classification criteria [26]. Later work used the results of a rock-detection system to choose targets for an infrared spectrometer [27]. Other researchers have made similar efforts, using rock characteristics to asses the merit of a target and re-plan a traverse [28].

Prioritization of targets for imagery or instrument targeting is greatly aided by identification of the target material. Work in parallel with the rock-detection efforts has investigated rock classification. This has largely been limited to the case of loose rocks sitting on the ground surface, and has used a variety classification parameters including shape, colour, albedo and other image-derived features, as well as infrared spectrometry (e.g. [29], [30], [31]). A further development was an attempt to build up a geological map by detecting changes in the assigned
classification of the rocks over the course of a traverse, in an effort to find boundaries between geological units [32].

Other work has attempted to apply visual geological classification to soils and unconsolidated material on the surface, such as gravel, sand, and other loose materials. Visual texture analysis has been applied to this problem [33], and recent efforts saw an attempt at reducing the computational power required [34].

Current work aims to use texture-based classification on solid material to identify particular biogenic structures for astrobiology survey [35], an approach which has shown promise in classifying surfaces using a machine-learning technique ([36],[37]). Many other types of material can in principle be studied using similar approaches.

In light of the difficulties in obtaining information from imagery in order to prioritize images, at least one effort examined a content-independent metric, correlating compressed image size to scientific merit as ranked by geologists [38].

2.2.2 Machine learning

The challenges of interpreting geological imagery — complex and varied appearance, a diversity of visual cues, complicating noise components, gradational boundaries, and visual similarity between different materials — mean that producing a direct, analytical algorithm to discriminate between rock types is very challenging. Unlike elementary computer vision tasks, a simple thresholding or differencing operation cannot, in general, allow a useful segmentation into rock types. Even in such elementary cases, prior knowledge of the scene is necessary, for example to allow a value of the threshold to be chosen. But for geological imagery, the visual complexities mean that the discriminant values of visual features are difficult to know – for example, which colours are useful to tell one rock from another, or which albedo differences indicate lithological differences, and not just internal variation within a rock type? In fact, given the diversity of rocks and of their appearances, the space of such features is very large. Not only are the discriminant values of given features difficult to know, but even the choice of

features is challenging.

Nonetheless, human geologists use visual cues to detect differences between rock types. While reproducing the visual cues they use by direct analytical programming is difficult, the feature choice, and discriminant values, might be discoverable. In similar cases in medical imaging, machine learning approaches have proven fruitful in discovering useful information in high-dimensionality spaces of visual features (see section 2.1.2 above). Current work on geological imaging has also begun to explore this class of techniques [37].

Machine learning represents a class of optimization techniques in which performance is improved by consideration of knowledge gained by experience in operation [39]. In general, these techniques seek to discover a suitable criterion for decision-making based on the outcome of past decisions. A broad range of approaches has been developed, often driven by the variety of applications to which they have been applied. Image interpretation is among the domains where this class of techniques have been applied, with a great vareity of approaches, generally driven by specific image interpretation problems [40]. These include, for example, classification (pixel-wise or of whole scenes), segmentation, object recognition, event detection, and novelty detection.

Two broad categories of learning approaches exist [41]. In *supervised learning*, the learning algorithm is provided with information about the particular classes into which the data is to to be divided. In image processing, this can take the form of labeled pixel data, where the user provides a set of training data augmented with descriptions of which class each pixel *should* be assigned. In contrast, *unsupervised learning* aims to discover structure in data, such as class distinctions, without the guidance of labeled data. These approaches often rely on discovering statistical groupings and correlations within the data, and clustering groups of data points within an *n*-dimensional *feature space* composed of the *n* types of quantifiable attributes, termed *features*, associated with the data.



Figure 2.1: Illustration of a distance metric and discriminant surface for data in two classes. For the blue and orange data classes, distance along the vertical axis is a useful metric of class membership. As the value of 10 along this axis divdes the classes well, this is a useful discriminant surface.

2.2.3 Distance metric learning

A simple approach to classification is by using absolute position in the feature space as a means of discrimination. Figure 2.1 shows a dataset with two coloured classes; position along the vertical axis could be used to discriminate between members of these two classes. That is, distance along the vertical axis can be used as a metric for class membership. *A priori*, the value of 10 on this axis could be selected as the boundary value for classification according to this distance metric. In many types of classification problems, however, the position of this boundary (or, in general *n*-dimensional terms, the *discriminant surface*) is not known. Such is the case for possible feature spaces composed of visual information relevant to geological segmentation. If, for example, albedo, colour, and visual texture were used to make a feature



Figure 2.2: Rock outcrop showing different, adjacent rock types which can be readily noticed by visual cues. The rock types are within themselves visually uniform, but vary from each other, in such features as albedo, colour, and visual texture. This outcrop is an example of the Ministic Lake emplacement of breccia at the Sudbury impact structure, of scientific interest because of the arrangement of the materials and what they reveal about emplacement during crater formation.

space for classifying an arbitrary image of a rock outcrop, such as that in Figure 2.2, it is very difficult to determine, *a priori* or from the physics of the problem, the values to use for discrimination. This problem of choosing the positions of discriminant boundaries within the feature space becomes even more difficult as the number of classes increases, or as their differences become less pronounced and the number of types of information needed to separate them (the dimensionality of the feature space) grows. *Distance metric learning* allows the algorithmic estimaton of such distance metrics and corresponding discriminant surfaces [42]. By these techniques, it is possible to learn appropriate distance metrics for a feature space automatically, though a degree of supervision may be necessary for the learning process. A

number of techniques exist for such metric learning, of which a thorough review is given by [43].

2.2.4 Linear Discriminant Analysis

One well-established type of metric learning for classification is Linear Discriminant Analysis (LDA), which has shown good performance across a variety of cases and criteria [43]. LDA seeks to find a linear transformation matrix, *A*, which when applied to data vectors in the feature space, maximally separates vectors representing different classes, and reduces distance between vectors belonging to the sample class. Applying *A* to the data vectors represents a linear transformation of the feature space, projecting it into a new vector basis.

The squared distance between two vectors x_i and x_j as measured in this new basis is (after the notation of [43]):

$$d_{M} = (A^{T}x_{i} - A^{T}x_{j})^{T}(A^{T}x_{i} - A^{T}x_{j})$$

= $(x_{i} - x_{j})^{T}AA^{T}(x_{i} - x_{j})$ (2.1)

The projection matrix A is found by maximizing the between-class variance and minimizing the within-class variance of the labeled classes, optimizing the objective function:

$$f(A) = \frac{\det(A^T B A)}{\det(A^T W A)}$$
(2.2)

where B and W are respectively the between- and within-class scatter matrices. In preparing distance metrics for a feature space, LDA uses the Mahalanobis distance [44], which for a data point whose candidacy in a class of points is in question, normalizes the Euclidean distance of a that point to the magnitude of the class variance in the direction of the class centroid. This normalization allows a meaningful and adaptable scale for the distance metrics to be obtained.

Figure 2.3 illustrates the concept of finding an ideal vector basis to discriminate between



Figure 2.3: Illustration of finding an ideal vector basis. A distance metric in the direction of y_2 is much more useful to separate the three coloured classes than along y_1 . The axes are also scaled, to represent the adaptive scale with respect to class variance along the axis given by the Mahalanobis distance.

classes. For the data points, coloured to represent three classes, the vertical axis is not as useful a distance metric as it was in Figure 2.1, since points at a range of distances along it can belong to any class. However, distance along the axis y_2 is a very good metric. Since the Mahalanobis distance is normalized to class variance along the axis, y_2 is scaled to a smaller linear length; x_2 is scaled longer, since the intra-class variance in that direction is large (illustrated by the large spread of data points in that direction).

As suggested in Figure 2.3, LDA can be generalized to the case of discriminating between greater than 2 classes [45], in which case it is called Multiclass Discriminant Analysis (MDA).

2.2.5 Data clustering

Given a set of feature vectors, one approach to assigning the data to classes is data clustering. In these approaches, it is generally the goal to classify data points based on their similarity in regards to salient features, or formally expressed, their proximity in relevant dimensions of the feature space. Many types of data clustering algorithms exist, of which one of the most established is k-means clustering [46]. These algorithms depend on iterative techniques to find groups of data points clustered near each other within the feature space.

K-means clustering is named because in this method the number of classes, *k*, is specified, and because the algorithm iteratively assigns data to classes clustering around optimal centroids approximating the mean position of class members. Initially, *k* cluster centroids are selected at random from among the data $x_1, ..., x_n$ to be clustered. The classification proceeds by optimization of:

$$\min_{\{m_q\}, 1 \le q \le k} \sum_{q=1}^k \sum_{x \in C_q} |x - m|^2$$
(2.3)

where $m_q = \sum_{x \in C_q} \frac{x}{n_q}$ is the centroid of cluster C_q , which has n_q elements. As an iterative process, data points are assigned to the cluster of the nearest centroid, after which a new centroid is computed based on the positions of the member points. The process iterates, with all data points reassigned to the closest of the newly-comuted centroids on each iteration until the process converges.

The simplicity of the *k*-means algorithm is appealing, and it has seen wide use. Though it can converge to local minima, this can generally be avoided by running the process several times starting from different randomly-selected seed centroids at the first iteration. It does require specification of the class number; other classification techniques exist which can estimate the number of classes in the data, but these generally require specification of several additional parameters relating to, for example, thresholds for similarity and difference in creating new classes.

2.2.6 Evaluating segmentations

The goal of the geological segmenter is that it should produce a pixelwise map of the image corresponding to semantically meaningful differences in visible geological type — that is, its division of the image should correspond to the real distribution of rock types. There is, of course, no reference information for the real distribution of rock types, so the segmentation must be compared to a human interpretation of the image. And, indeed, the intended function of the segmenter, in a robotic autonomy scenario, is that it replaces the need for image interpretation by experts on Earth. This means that the goal is in fact to segment scenes similarly to the way a human expert on Earth would, making a human segmentation the appropriate reference for assessing the computed segmentation.

A qualitative comparison can be readily made, from the appearances of the image and computed segmentation, or from the computed and reference segmentations. A quantitative assessment is also possible, however. For vector clustering problems, the Adjusted Rand Index (ARI) is commonly used to find the similarity of two clustering solutions, by counting the number of pixels with are assigned to the same cluster in both the reference and the candidate clustering [47].

For image segmentation, the basic Rand Index is calculated by considering pairs of pixels. Suppose we consider two pixels in the image which both represent the same rock type. In both the reference and computed segmentations, they should be assigned to the same class. Similarly, if these two pixels belong to different rock types, they should be assigned to different classes in both the reference and computed segmentations. If the segmentation algorithm computes a perfect map of pixels, then every pair that we might consider will be of the same assignment case in both the computed and reference segmentations — in the same class when the reference has them so, in different classes when the reference assigns them that way. We might say that all pairs, in this case, are 'likewise-assigned'. But a poor segmentation will have many pairs of pixels for which this is not the case — pixels which should be together in a class are not, or which should be in separate classes are instead in the same one. These options are

Segmentation	Computed	
	Pair in	Pair in
Reference	same class	different classes
Pair in same class	а	b
Pair in different classes	С	d

Table 2.1: Contingency table for assessing segmentations

laid out in Table 2.1.

The basic Rand index is simply the fraction of pixel pairs which are 'likewise-assigned':

$$RI = \frac{a+d}{a+b+c+d}$$
(2.4)

This index is simple and useful, but suffers from two known problems. First, its expected value is not constant, and varies based on the number of classes. Second, and more importantly, it will tend to to give numbers closer to unity as the number of classes increases [47]. The widely used [48] Adjusted Rand Index (ARI) normalizes the Rand Index to random chance, and (for a comparison over n pixels) sets the expected value to zero.

$$ARI = \frac{\binom{n}{2}(a+d) - [(a+b)(a+c) + (c+d)(b+d)]}{\binom{n}{2}^2 - [(a+b)(a+c) + (c+d)(b+d)]}$$
(2.5)

The ARI for a randomly-generated segmentation will, on average, have the value of zero. For a perfect segmentation where all possible pixel pairs are likewise-assigned, it has the value of one.

The main limitation in using the ARI for assessing geological image segmentations is that it requires the preparation of labeled reference data, and its value will depend on reliable reference segmentations. It has the advantage, however, of providing a quantitative desription of the segmentation performance, by comparison to a reference which represents the actual desired task.

2.2.7 Approach

The visual heuristics used by field geologists to notice the presence of different, adjacent types of rock include albedo, colour, and visual texture, among others. An example of a rock outcrop showing contacts detectable by these visual cues is shown in Figure 2.2 (see section 2.2.3). This is an outcrop of the Ministic Lake emplacement of impact breccia from the Sudbury impact structure in northern Ontario, Canada; it is of scientific interest to studies of impact crater formation and the process by which materials are transformed and emplaced during the violent processes following the impact.

To the human eye — even that of a non-geologist — it is apparent that there are visible differences in this rock outcrop, suggesting the presence of several types of adjacent materials. While the geological and geochemical meaning of these may not be apparent, their visual distinctiveness is readily noticed. A dark band of material traverses the scene almost vertically, right of centre — within it, small pieces of lighter-toned material are embedded. This breccia vein is surrounded by a host rock with its own internal differences — some regions are pink in colour, others more white; some have a smooth visual texture, others appear rougher or mottled.

It is difficult to quantify the differences seen in the image — which levels might be set for brightness thresholds, which colour information would best serve classification. But what can be noticed are correlations — adjacent regions often differ from each other in more than one of these visual cues (both rougher and darker, both brighter and more reddish, for example). Figure 2.4 shows examples of simple image processing techniques applied to this image - the distinct regions noticeable to the human eye often stand out from their neighbours under several such operations. The approach to geological segmentation described in this work relies on the formalization of this observation: that different types of rock are generally visibly distinct from their neighbours in several visual aspects, simultaneously. The groups of pixels representing each of these regions of rock can be expected, then, to cluster in their values of brightness, colour, or other features into distinct groups from their neighbouring materials.



(a) Colour photo of the Ministic Lake breccia



(c) JPG red channel



(e) JPG blue channel



(g) Blue-Red difference



(b) Grayscale mapping of breccia image



(d) JPG green channel



(f) Blue/Red ratio



(h) Image gradient followed by 3-radius-sum kernel

Figure 2.4: Several examples of elementary image-processing techniques applied to the image of the Ministic Lake breccia outcrop. Together, these processed images form a possible feature space, of use for classifying the regions of the image.

The strategy is to generate a feature space which incorporates several types of useful visual information, derived from simple image processing techniques. In order to best use this feature space for classification, Multiclass Linear Discriminant Analysis is used to perform supervised learning that, given labeled exemplar scenes of rock outcrops, finds a linear transformation of the feature space which maximally separates the salient classes. With the feature space thus transformed, vector clustering by *k*-means can be used as an unsupervised classification step, to find groups of pixels corresponding to distinct classes of material. Pixels are then assigned to rock classes based on their cluster membership.

The learn-transform-cluster approach described above can be used to segment an entire image by labeling only a small fraction of the pixels. Of greater interest, it can also be used to label new images containing similar materials to the classes labeled in the training data. This affords the possiblity of using it during robotic exploration of planetary surface environments, as a rover images new, previously unseen outcrops displaying materials similar to those earlier identified by its science team.

The implementation of a computer vision algorithm to segment images of rock outcrops is presented in Chapter 3. The potential implications and applications for science autonomy in robotic exploration of planetary surfaces is discussed in Chapter 4.

2.3 Atmospheric applications: Tracking clouds

From the outset, atmospheric studies have been a natural part of the integrated study of planetary science, alongside orbital mechanics, dynamics, geology, and geophysics [49]. The composition, dynamics, and evolution of a planet's atmosphere are a main driver for that planet's surface conditions, climate, and weather. These in turn have important implications for surface processes studied in geology, and give hints to the planet's formation and subsequent evolution. For a surface mission, the weather can influence operational plans, restrict activities during inclement conditions, and affect the lifetime and power budget of a mission [50], especially if it relies on solar power [51]. For such a mission focused on understanding the geology and geochemistry of the landing site and its surroundings, the prevailing winds, both at local and regional scales, can give clues to numerous processes of interest. These might include the nature of erosion to which the surface is exposed, the sources of materials brought by aeolian transport, and connections to distant reservoirs of material, moisture, or heat that may influence the evolution or preservation of surface features. For any surface mission, the dynamics of the winds [52] and behaviour of the upper atmosphere [53] are among the main sources of uncertainty in trajectory planning for the spacecraft as it enters and descends through an atmosphere for landing.

As the most common visible feature in the atmospheres of Earth, Mars, and planets generally, clouds are a primary candidate for imaging work in atmospheric science. They have long been difficult targets for automated image processing because of their highly variable shape and texture, continuously changing appearance, and irregular boundaries [54]. However, their motions are a useful proxy for wind speed and direction [55], and this has led to efforts in cloud tracking in cases where other means of measuring wind are not available.

On Earth, surface winds are routinely monitored by networks of meteorological stations, while radiosondes and aircraft have historically provided information on winds aloft [56]. Such facilities are rarely available on other planets. A recent exception was the Phoenix Mars lander mission, which carried a suite of meteorological instruments to Mars' northern latitudes in 2008 [57]. This suite included a mechanical anemometer [58], which allowed measurement of the winds both for meteorological investigations, and support to other spacecraft operations [59].

2.3.1 Remote sensing

For planets where surface landers are difficult or impossible, in-situ wind studies are difficult to achieve. Here, cloud-tracking has been used to study wind motions, often at very broad scales. As early as the mid-1970's, Suomi and Krauss [60] were applying manual cloud-

tracking techniques to images of Venus from the Mariner 10 probe. Further work was possible by 1982, when Limaye and colleagues used images of clouds from the orbiting Pioneer Venus spacecraft to study global wind patterns [61]. This technique was refined over subsequent years [62] as the spacecraft gathered more data [63], allowing the inference of global and zonal circulation patterns. [64] and others ([65], [66]) applied similar techniques to eddies and zonal flows on Jupiter, and on Saturn [67], using images from the Voyager 1 and 2 probes. These efforts continued to rely on manual inspection of images, at great investment of time and effort.

2.3.2 Automated efforts

Later work attempted to automate the process, with initial efforts to apply computers to the problem giving results early on [68]. After many years of development, by 1990, a first fully-automated process was available [69]. Manual techniques continued to outperform the automated efforts for many uses; Vasavada *et al* [70], for example, applied a mix of manual and automated techniques, to study vortices and other features in the atmosphere of Jupiter. Development continued, however, with Luz *et al* [54] presenting an automated method for tracking clouds in planetary atmospheres. This system was applied to images of the atmosphere of Jupiter and used for deriving the rotations of vortices and eddies; it was later adapted to the southern polar vortex of Venus [71], allowing a new understanding of flows in the atmosphere's polar regions [72]. A recent example of such a fully-automated technique is presented by Choi *et al* [73]. The algorithm tracks features across image pairs by a technique of sampling multiple sub-sections of the later image and finding the maximum cross-correlation to each identified feature of interest in the earlier image [74]. This allowed the generation of vector fields for the winds in several weather systems in the atmosphere of Jupiter, giving new insights into the dynamical structures and energy exchange processes at work [75].

The technique of cloud-tracking for global and zonal winds has been most extensively applied to the Earth, particularly using imagery from satellites of the GOES [76], GMS [77], and Meteosat [78] series. Such systems became reliable and accurate enough to be used for

operational weather forecasting by the late 1990s [79]. The extensive research for the Earth case has allowed continual improvement in accuracy of the wind fields obtained ([55], [80], [81]), and revealed details of the utility of the technique. A key limitation, for example, is the tendency of cloud-drift-derived wind fields to underestimate the high-speed winds associated with jet stream areas [82]. They are also, of course, limited to areas where clouds have formed.

2.3.3 Surface-based work

The applications described above, at Earth, Venus, Jupiter, and Saturn, stem from the successful use of cloud-tracking techniques in looking at planetary atmospheres from above. Such observations study winds at altitude at large scales of hundreds to thousands of kilometres, while conventional surface measurements provide point observations at the surface. Moores *et al* [83] showed a method for studying winds at the cloud height when orbital observations were not available. This work used the Surface Stereo Imager (SSI) camera on the Phoenix lander to capture sequences of images of clouds above the landing site. By visual investigation of the sequences, cloud features could be identified and their motion estimated, giving a way of determining wind direction at the time of the observation. The image analysis in this case was entirely manual, with no automated cloud-tracking techniques applied.

Another research group has conducted similar work on Earth. As part of a European Union (EU) Fifth Framework Programme (FP5) project called Cloudmap2, Seiz *et al.*[84] developed an algorithm for automated cloud tracking using ground-based cameras. This work was a necessary tool for studying cloud dynamics in a project whose overall goal was to better characterize the radiative absorption and scattering behaviour of clouds, to enable the production of better weather and climate models [85]. The technique was used as a stereo implementation to produce 3D models of clouds by matching images from two cameras on the ground, combined with remote-sensing imagery from satellite instruments, but the authors noted its utility for following clouds through time sequences as well. The work on this project was concluded with the end of the FP5 programme. Such work does not appear to have been further

developed for Earth applications, nor adapted for clouds in the atmosphere of Mars.

2.3.4 Approach

Obtaining the wind vector from cloud motion in sequences of zenith-aimed images, as in [83], can be treated as a computer vision problem of object tracking. The significant variability in the appearance of clouds, however, does not allow for a simple object-detection algorithm to be developed. Alternate techniques using visual feature detection, such as Speeded Up Robust Features (SURF) [86], Scale-Invariant Feature Transform (SIFT) [87], and Random Sample Consensus (RANSAC) [88], rely on persistence of the detectable features from frame to frame. Finding such persistent features has been challenging [89]. While Mukherjee and Acton [90] had success by following such features in imagery acquired from Earth orbit of clouds over scales of hundreds to thousands of kilometres, at the fine scales seen in imaging from below, the details of the boundaries of clouds change rapidly, even on the timescales of tens of seconds. In the images of Figure 2.5, the same cloud has persisted over tens of seconds, but the details of its edges, and aspects of its overall shape, have changed significantly. Feature-tracking would be a very challenging approach for such images.

For imaging from orbit, clouds exhibit slow change in their detailed features, translation, rotation, and shearing motions. For clouds seen over a small field of view imaged at zenith, these motions are simplified — the clouds can be taken to move with a single translational vector, as a bulk motion, even while fine-scale changes continuously occur. On these scales, then, the goal of observing the wind direction at the cloud altitude is achieved by finding the bulk motion.

To this end, the problem is reconsidered as one of image registration with scene variability. This is a very common problem in terrestrial remote-sensing studies, where images of overlapping terrain must be aligned to a common georeference to produce maps or allow time series comparisons [91]. In these cases, variation can occur in the appearance of same scene imaged at different itmes by a satellite or aircraft, for example due to differences in cloud cover or to



(a) t = 0 s



(b) t = 120 s



(c) t = 240 s

Figure 2.5: Sequence of cloud images showing the rapid change of fine-detailed features, but slow evolution of overall shape. Images acquired from the ground with zenith pointing.



Figure 2.6: Principle of image cross-correlation. A portion of the right-hand image, the template, is checked for similarity with each position at which it may be overlain on left-hand image, the target.

the changing aspect of the land with the seasons. Such changes in detail despite preservation of overall shapes is analogous to the behaviour of clouds on the length and time scales shown in Figure 2.5.

An established technique for addressing this registration problem is image cross-correlation. Here, a portion of one image, called a template, is compared for similarity to all regions of a target image thought to contain the same region. A similarity metric, the correlation coefficient, is computed for each pixel position, with the highest coefficient being found at the position where the template matches the overlain target image most closely (illustrated schematically in Figure 2.6).

After the notation of [92], the correlation coefficient between the template $T_{i,j}$ and target $G_{i,j}$ is calculated by:

$$C(T,G) = \frac{\sum_{ij} (t_{ij} - \text{mean}(T))(g_{ij} - \text{mean}(G))}{\sqrt{\sum_{ij} (t_{ij} - \text{mean}(T))^2 \sum_{ij} (g_{ij} - \text{mean}(G))^2}}$$
(2.6)

where t_{ij} are g_{ij} as the pixel values of the template and target, at row *i* and column *j*. This correlation coefficient has the value of 1 for identical images, and normalizes for brightness variation by the incorporated mean subtraction. Its computational cost is of order N^2 for a template of *N* pixels [92].

The implementation of a wind-vector estimation technqiue based on cloud-tracking using

normalized cross-correlation is described in Chapter 5. An assessment of currently-available upper winds information obtained by zenith imaging on the Mars Science Laboratory (MSL) mission is given in Chapter 6, along with a proposed strategy for robotic autonomy to improve the acquisition of this data during future surface operations.

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Chapter 3

Autonomous Mapping of Outcrops Using Multiclass Linear Discriminant Analysis

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3.1 Introduction

Planetary exploration missions have deployed progressively more capable and complex platforms to explore the bodies in the solar system. The Mars Science Laboratory rover, for example, carries an extensive suite of remote-sensing, contact, and internal instruments [1], together offering far greater capacity to generate scientific data than previous missions. Communications capabilities continue to be an important limitation for these missions, however, restricting the amount of data that can be returned to Earth. This has an additonal consequence of restricting the speed of operations, as many tasks – such as approaching a rock outcrop and placing an instrument against it – require several human-in-the-loop steps in decision-making. Each such step requires the transmission of data to the Earth, its inspection, and the transmission of resultant commands to the spacecraft.

3.1.1 Improving scientific throughput

These missions could realize a greater throughput of science information by achieving these tasks more quickly, or by devoting a larger fraction of the downlink to science-relevant images as opposed to intermediate images intended for human decision-making. Achieving either – more science per time, or more science per kilobit – may be possible by allowing the robotic system to make decisions on its own.

One tool for aiding such decision-making by the robot is autonomous interpretation of images. A major task of operations scientists is finding interesting features in downlinked images so that they may be targeted for further investigation. New software has already begun to allow a degree of autonomous interpretation and improved scientific return, as in the case of the AEGIS software developed for the Mars Exploration Rovers [2], which uses on board image processing to prioritize images for downlink, based on the detection of rocks sitting on the plain surrounding the rover.

3.1.2 Geological investigations: In-place materials and contacts

For a surface mission with a geological focus, an example of an interesting feature is an outcrop in which visual inspection suggests the presence of more than one type of rock. In terrestrial field geology, these features are called *contacts* between *geological units*, and while they have a variety of forms and origins, they are important sources of information about the nature and history of the rocks in a region. The information they carry is particularly rich if the materials are still *in-place*, that is, remaining in the position and context of their formation. This makes outcrops valuable sites of investigation, over loose material that cannot be clearly connected to its place of origin.

Impact craters, ubiquitous on solid planetary surfaces and of interest for both geological and astrobiological investigations [3], are formed by violent and turbulent processes that result in numerous emplacements of mixed rock types, such as impact breccias, melt rocks, and ejecta deposits [4]. This chaotic process also tends to produce features of vertical relief, often

including exposed outcrops of rock, particularly in environments where the rate of erosion is low. Finding such outcrops, particularly those displaying geological contacts, is critical in investigations of such widely-varying settings as impact craters, sedimentary environments, and volcanic flows.

3.1.3 Present work

The present work aims to develop image processing tools which allow the segmentation of images of rock outcrops along geological units, as a step towards producing a capability for detection and mapping of outcrops displaying geological contacts. We formalize this problem as one of unsupervised image segmentation into geologic surface types. We test the hypothesis that Mahalanobis metric learning, trained by exemplar scenes, can improve the fidelity of such segmentation produces geologically relevant categories from simple colour and texture primitives when analyzed with appropriate distance metrics. Section 3.2 describes the history of similar work in the exploration context. The design of the algorithm is presented in section 3.3, and the design of an experiment to test it is described in section 3.4. The results of tests on field data in a variety of geologic settings are presented and discussed in section 3.5.

3.2 Existing techniques

3.2.1 Geological classification

Geology on Earth relies on site visits by a trained analyst, but planetary exploration programs have researched automated techniques. Previous efforts have identified specific features in outcrops, especially sedimentary layering [5],[6]. Further efforts saw significant successes in detecting loose rocks resting on the ground [7],[8], by a variety of techniques with varying results [9]. Such systems eventually became capable enough to be used to guide robotic decision

making [10], and in recent years to be deployed on the Mars Exploration Rover Opportunity to improve the return of scientific data [11]. But with highly variable visual appearance, gradational boundaries, and complex boundary morphology, separation of geological materials within an outcrop is even more challenging a task than recognizing rocks against a background. At least one current project is working to apply information from image texture to the problem [12] but to our knowledge the present work is the first attempt to identify geologic contacts within a single image in a wholly unsupervised fashion.

3.2.2 Distance metric learning

In the presence of correlations and noise dimensions in the input space, it can be quite difficult to find a representation where the classes of interest naturally separate from each other. Metric Learning seeks a distance metric, or equivalently, a transformation of the input space, to maximize task performance. These methods typically rely on a training set of distinct classes from the problem domain. They optimize the distance metric to maximize the distance between the dissimilar classes. This new representation reflects semantic distinctions of interest so that a wholly unsupervised algorithm can recover them (though the initial learning step used to find the new representation requires, in this case, a supervised learning approach).

Many such algorithms involve fitting a Mahalanobis metric, expressed as a simple linear projection that we will write here as a matrix A. Following the notation of [13], applying A to each sample pair (x_i , x_j) produces a Mahalanobis distance in the original sample space:

$$M(x_i, x_j) = (A^T x_i - A^T x_j)^T (A^T x_i - A^T x_j)$$

= $(x_i - x_j)^T A A^T (x_i - x_j)$ (3.1)

Note that the matrix $M = AA^T$ is symmetric, positive semi-definite. There are many ways to find this matrix. The most common approach, Multiclass Discriminant Analysis , is an extension of classical Linear Discriminant Analysis (LDA); for k distinct classes, it forms A by the eigenvectors associated with the top k-1 eigenvalues of $M_w^{-1}M_b$ Here M_w is the within class scatter matrix and M_b is the between class scatter matrix. The resulting transformation minimizes the determinant of the former and maximizes the determinant of the latter. Other linear distance metric learning algorithms include Information Theoretic Metric Learning [14], Locally Discriminative Gaussians [15], and Neighbourhood Components Analysis (NCA) [16]. A comparison of all such techniques is beyond the scope of this paper, but LDA-based methods often perform comparably to iterative approaches and basic MDA is sufficient to evaluate our hypothesis.

3.3 Method

3.3.1 Strategy

The approach used in this work begins from the observation that rocks which are visually distinct from each other are often distinct in several ways - by colour, by the orientation of linear features in the rock surface ('fabric', in the geological sense), or visual texture, such as from layering, weathering, fracturing, or grain size. Very often, separate geological units are visually distinguishable from each other in more than one of these characteristics. We attempt to exploit this property by applying a technique that finds groups of pixels which vary together in several visual features.

3.3.2 Channel set

We begin by processing an image to produce several data products relating to colour, texture, and other visual attributes at each pixel. Each such data product is called hereafter a visual *'channel'*, and represents an array of values corresponding to each pixel in the input image. For initial tests, a basic feature set was used consisting of seven channels:

- 1. The grayscale representation of the colour image;
- 2. The red channel of the colour image;

- 3. The green channel of the colour image;
- 4. The blue channel of the colour image;
- 5. The ratio, at each pixel, of the blue and red channels;
- 6. The difference, at each pixel, of the blue and red channels;
- 7. A brightness map produced by first taking the magnitude of the image gradient at each pixel, then passing a kernel over the result which sums the values of all pixels in a small radius. This channel is intended to respond to the local density of edge features in regions of the image.

An extended feature set uses these same channels along with eight more provided by the MR8 filter bank [17], in an effort to further emphasize textural information. In principle, many more channels can be designed and included, but this present work reports only on results using the above basic and extended feature sets.

For either implementation, the data produced in creating the *n*-dimensional feature space is represented as a set of *n*-dimensional vectors, with each pixel represented by a vector composed of that pixel's corresponding values from each visual channel.

3.3.3 Learning step

We first train MDA by using a dataset of labeled images from the same locale. This is relevant for spacecraft operations where a rover is travelling tens or hundreds of metres per command cycle, and geologic surface types will be somewhat similar to categories that have already been seen in previous images. Scientists could train such a system on the ground and then transmit the compact transformation matrix to the rover, enabling it to recognize appropriate features in new images. For each set of training data, we formed 2 to 3 classes from the categories of interest, and learned an MDA representation based on this training data. MDA permits solutions with a rank up to k-1 where k is the number of classes. We then applied the lowrank transform to other images from the locale not used during training, producing an unbiased estimate of task performance on a new scene.

To effect the segmentation, the feature space vectors are transformed to the MDA-learned representation, then clustered by proximity in the *n*-dimensional feature space. As a baseline, the k-means clustering technique is used, with other clustering techniques possible.

3.3.4 Assessing the segmentation

Candidate segmentations are assessed by comparison to manually-labeled reference segmentations using the Adjusted Rand Index [18]. The Rand Index is a figure of merit that counts the number of pairs of pixels which are, in both segmentations, assigned to the same segment, as a fraction of the total number of pixels. Normalized against random chance, it becomes the ARI, which has a value of zero for a pixel segmentation performing the same as random assignment, and a value of one for a segmentation which is identical to the reference.

3.4 Experiment design

The technique was tested on imagery from a variety of geological settings, including several types of volcanic deposits in Mars-analogue sites in the Mojave desert, California; impact breccias from the Sudbury impact crater in Ontario, Canada; and a clay-rich sedimentary setting with visible calcium sulfate veins in Gale Crater, Mars. In each geological setting, the system is trained using a representative image showing the characteristic local rock types. The trained system then segments both the training image, and new images from the same locality. Three cases are tested in each locality, each using a different feature space:

- The basic feature space (described in section 3.3.2), without applying the learned vector ("No learning")
- The basic feature space, with the learned transformation applied
• The extended feature space including the MR8 filter bank, with MDA learning on that larger space

In each case, the segmentation is compared to a reference, human-labeled segmentation, using the Adjusted Rand Index.

For the locales on Earth, the photographs used were captured with a handheld digital SLR camera. Lighting conditions varied from full insolation to full shade; cast shadows that covered only a portion of the scene were avoided, though shadows created by in-scene relief are unavoidably present in several cases. The photographs were selected to show a variety of geological materials with visible contacts, and a variety of contact types (sharp, gradational, highly complex), and morphologies (adjacent massive units, layered materials, clasts within a matrix). Artifical objects often included in geological imaging, such as hammers and rulers to provide a reference for scale, were intentionally excluded. These procedures allowed the experiment to employ a set of fully natural scenes with no intrusions, but somewhat optimized shadow for the local topography. Such conditions are representative of those to be expected in planetary surface imaging with a robotic platform.

Images from Mars were obtained by the left and right Mastcam imagers of the Mars Science Laboratory rover in the context of the mission science team's investigation of the Yellowknife Bay locality of Gale Crater. Scenes of the desired lithologies having broadly similar dust cover were selected from the area visited by the rover on sol 133 of the mission, with views of the rover hardware excluded.

3.5 Results

We tested the algorithm on a variety of scenes having diverse rock types and boundary shapes. These scene types are described in the following section, and include a variety of volcanic, impact, and sedimentary settings, each showing clear contacts between distinct geological units.

The results of the segmentation are shown in Table 3.1. For each scene type, one image

Table 3.1: Segmentation algorithm performance.	Values are the Adjusted Rand Index,	as described in
section 3.3.4		

Scene	Number	Image	No learning	Learning on	Learning
type	of classes	reference		basic feature	on extended
				space	feature space
A	2	1277	0.814	0.968	0.987
		1261	0.912	0.922	0.936
		1281	0.912	0.961	0.973
В	2	0272	0.562	0.759	0.816
		0743	0.378	0.657	0.715
		0283	0.348	0.538	0.609
С	3	0199	0.565	0.943	0.950
		0200	0.372	0.795	0.749
		0230	0.245	0.587	0.563
D	3	0495	0.323	0.693	0.742
		0497	0.289	0.616	0.633
		0511	0.350	0.589	0.665
Е	2	9726	0.774	0.920	0.946
		9735	-0.072	0.790	0.793
		9745	0.761	0.837	0.868
F	2	s133r1	0.084	0.769	0.828
		s133ls2	0.053	0.220	0.718
		s133ls3	-0.002	0.018	0.313



Figure 3.1: Example of scene type A. Basalt blocks and sand, image number 1281, and its segmentation result.

of a representative scene was used to train the algorithm. The feature space transformation learned using this image was used in segmenting this same image, and two more images of the same type of geological materials, taken under similar lighting conditions at an adjacent site, with the image fields of view not overlapping that of the training image. For each scene type, the image used for training is that marked by by an italicised reference number in Table 3.1. Examples of labeled scenes are given in Appendix A

3.5.1 Scene types

Type A: Basalt blocks and sand

A mixture of irregular, vesiculated basalt blocks, surrounded by fine sand, shown in Figure 3.1. The basalt blocks are of volcanic origin. The silicate sand occupies the space between the basalt blocks, and also fills in some of the surface vesicles, complicating the segmentation.

Type B: Massive basalt and lahar deposit

Outcrop exposure of massive basalt overlying older lahar deposit, shown in Figure 3.2. A lahar deposit, formed by violent pyroclastic flow, is visible in the lower portion of the image as a highly disordered accumulation of material with many irregular shapes and highly varying



Figure 3.2: Example of scene type B. Massive basalt and lahar deposit, image number 0272, and its segmentation result.

colour and texture. It is overlain by a layer of massive basalt, sourced from a later volcanic event. The basalt also has non-uniform colour, and some of the surface coatings in the basalt are of similar colour to the lahar. Fissures and ridges that intruduce linear shadows are also present.

Type C: Layered volcanic deposits

A succession of volcanic deposits from periodic events at the Cima volcanic flows, shown in Figure 3.3. Three layers of material are visible. Each has a different dominant colour, but each shows significant variation. Gradational changes are visible between the layers, and some blocks in the bottom layer have faces which are coated in material from the top layer. The boundaries are irregular, and enclaves of each material can be found within the others.

Type D: Complex intermixed volcanic materials

A complex scene, treated as three distinct classes, shown in Figure 3.4. Massive basalt overlies, and is partially mixed into, two other types of material, each of which is visibly heterogeneous. Such visibly complex scenes are common in a variety of geological settings.



Figure 3.3: Example of scene type C. Layered volcanic materials, image number 0199, and its segmentation result.

Type E: Impact breccia

An exposed outcrop of breccia from the Sudbury impact structure, shown in Figure 3.7. Fractured by the violence of the impact, clasts of one type of rock are embedded in a matrix of another type. This type of material is common in impact craters and in volcanic settings.

Type F: Mineralized veins in Martian sandstone

An outcrop of clay-rich mudstone showing visible veins of calcium sulfate material [19], in the Yellowknife Bay locality of Gale Crater, Mars. This site was studied by the Mars Science Laboratory mission science team, and an example is shown in in Figure 3.10. It was selected as a high-priority science target, and a nearby outcrop of the same composition was the site of the first drill sample of the mission. The training image was acquired by the MSL rover's right Mastcam; the other two test images are of nearby exposures of the same material imaged by the left Mastcam, all on sol 133 of the mission. Significant and non-uniform coverage of reddish dust on both rock types, nearly ubiquitous on the Martian surface, complicates the vision problem.



Figure 3.4: Photograph of complex geological scene, image number 0495



Figure 3.5: Segmentation map of image number 0495

3.5.2 Discussion

In general, the algorithm produces good quality results, both by reference to the Adjusted Rand Index figure of merit, and by visual inspection of segmentation maps. Even without the learned transformation matrix, the system produces results significantly better than a random pixel assignment, and in some types of scenes, far better. With the learning step included, the figure of merit increases in all cases, generally by a significant margin. The value of the training is also illustrated in Figure 3.6, which compares the separation of pixel vectors as plotted using a principal components analysis, and reprojected using the MDA-learned feature space representation. The projection is trained on a separate image. When applied to the new scene, it improves the alignment between k-means clusters and geologic unit classes. Black circles show the locations of cluster centroids.

The expanded feature space, including the MR8 filter bank, in most cases produces only a small improvement over the results with the basic feature set. The MR8 filter bank is designed to contribute information about visual texture, as is the gradient-derived channel in the basic feature space. Given the small marginal improvement of the ARI in most cases, it appears that the gradient-derived channel adequately captures that textural information, for most purposes, and the high cost of computing the MR8 channels may not be justified in many applications.

As the scenes become more complex, with greater intra-class variation and complex boundaries between classes, the figures of merit are somewhat reduced. Nonetheless, even for very complex scenes, a visual inspection shows that the segmentation accurately reproduces the visual divisions that are salient to the human eye. An example of this is in scene type D, where three types of volcanic deposits are found in a single outcrop, with very complex mixing and irregular boundaries. Such a scene is shown in Figure 3.4, where a massive basalt, visible in the upper right hand corner, is intermixed with two different layers of volcanic material. The segmentation map for this image is shown in Figure 3.5. The division of the scene by material type is evident, with the algorithm detecting even small isolated regions of one material embedded in another. Some stray pixels are apparent, attributed to the difficulty of training on this very



Figure 3.6: Normalized spread of the pixel vectors with the learned feature space representation from MDA, compared to an ordinary principal components analysis. Data from image #0497, trained on #0495, coloured by class label.

difficult scene type. The Adjusted Rand Index for this segmentation is 0.742. While already likely adequate for a variety of follow-on uses such as steering a spectrometer instrument at the identified regions, futher improvements may be found by including new types of information in the feature space.

A particular demonstration of the value of the learning step is found in the case of the impact breccias from the Sudbury crater. Here the algorithm was, as usual, trained on a single example of a typical outcrop, then tested on other images of similar materials. One of these, with image number 9735, is shown in Figure 3.7. A reddish oxidation coating is visible on the surface of the outcrop. This uneven coating covers portions of both rock types (the darker-coloured ground mass, and the lighter-coloured clasts) in the breccia. This colouration is unrelated to the rock composition and potentially confusing to an algorithm relying on colour information, and without applying the learning step the results are unsatisfying. Figure 3.8 shows the segmentation map for the no-learning case, with ARI -0.072, slightly worse than random assignment. A naïve two-class clustering finds the numerically-significant difference



Figure 3.7: Photograph of Sudbury impact breccia, image number 9735



Figure 3.8: Segmentation map of image number 9735, without the learning step applied



Figure 3.9: Segmentation map of image number 9735, with the learning step applied

between the smooth rock and dark shaded fractures. However, with the learned feature space transformation applied, the results are greatly improved, as shown in Figure 3.9, with the ARI rising to 0.793, even with the algorithm having been trained on a different image in which the oxidation coating was not present.

The learning step also improves the sedimentary example from Yellowknife Bay, Mars. Reddish-hued dust is nearly ubiquitous on rock outcrops on Mars, and like the oxidation coating in Sudbury, is potentially confusing to a vision algorithm. The segmentation is greatly improved by the training, even in the most challenging case (image s133ls3), where significant variation in dust cover makes the host rock appear more grey, rather than the dominant red hue seen in the training image in Figure 3.10. The challenging variation in colour from the dust cover is likely the reason why this is the geological setting in which the extended feature space, featuring the texture-rich MR8 filter bank, is most beneficial.

3.6 Conclusion

Further testing in new geologic settings is ongoing. In particular, the system is being tested as a means of detecting surface contaminations – recognizing dust partially covering a rock outcrop, for example, and discriminating it from the rock itself – for application to images of dusty contact spectrometry targets investigated by the MSL rover. Future developments of the technique could expand and optimize the feature space to account for optimal combinations and representations of the colour channels. An adaptation to multispectral imaging, as currently practiced with Mars-surface missions, is also planned. The system could also be adapted to other imaging modalities, depending on the instrumentation available in a given setting. As part of integration into a larger scheme for outcrop analysis, an autonomous method for determining the number of classes to use in the vector clustering is also in development.



Figure 3.10: MSL MastCam-right photograph of calcium sulfate veins in mudstone, image reference s133r1. Image credit: NASA/JPL-Caltech/MSSS



Figure 3.11: Segmentation map of image s133r1

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Chapter 4

Autonomous Rock Outcrop Segmentation as a Tool for Science and Exploration Tasks in Surface Operations

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4.1 Progress and constraints in planetary exploration

Planetary exploration missions have seen continual progress in capability and complexity in recent decades, as programs have developed and technology has advanced. Flyby missions such as the successful Voyager 1 & 2 [1] were followed by capable orbiters with landers, as in Cassini-Huygens [2]. In the last two decades, global mapping and long-timescale surveil-lance of Mars has progressed with orbiter missions carrying ever-better instruments at visible wavelengths and across the EM spectrum, as Mars Global Surveyor [3] was succeeded by Mars Odyssey [4], Mars Express [5], and Mars Reconnaissance Orbiter [6], with more missions to follow. Current missions greatly exceed the capabilities of their predecessors. The European Space Agency (ESA)'s stunning success in imaging the nucleus of comet 1P/Halley with the Giotto spacecraft in 1986 [7], [8] will soon be followed by the Rosetta mission to approach, map, orbit, and land on the nucleus of comet 67P/Churyumov-Gerasimenko [9], as only one example of this progress.



Figure 4.1: A progression of landed rover systems. From smallest to largest, engineering models of the Mars Pathfinder, Mars Exploration Rover, and Mars Science Laboratory rover vehicles (with humans, for scale). Image credit: NASA/JPL-Caltech

This growth in the number and capability of missions has led to a wealth of new data and knowledge about our planetary neighbourhood, but also to challenges in data management [10]. This has led NASA to upgrade its Deep Space Network both to replace aging equipment and increase capacity [11]. Meanwhile the ESA, seeing a growing constraint in communication capabilities [12] has expanded its network of tracking stations to include three 35-m antennas [13] [14]. Both agencies are increasing cooperation to better use the assets which are collectively available [15]. Promising developments in optical communication over planetary distances [16] may increase the available bandwidth [17], but there will still be a limit to the data budget available [18], and individual missions will continue to experience bottlenecks.

Mars surface missions are a particular example of the growth of mission capability that has driven this expansion of the communications architecture. Over the last two decades, progressive improvements in entry, descent, and landing systems, vehicle design, and operational experience in conducting mobile missions on the surface of Mars have led to a growth in the scale of rover missions (Figure 4.1).

With larger vehicles came the capacity to accommodate larger and more complex payload systems – the Mars Science Laboratory (MSL) rover, launched in 2011, carries 75 kg of science payload [19], a more than tenfold increase over the Athena payload suite carried by the Mars Exploration Rovers (MER) in 2003 [20]. With more, and more complex, instruments comes the potential to generate a great deal of science data, but the communications system in place today is little changed since the start of the MER mission, giving constraints on the data that can be acquired.

Even by the time of the MER extended mission, innovative strategies to acquire more scientific information in data-efficient ways were coming into use. Uploaded in 2009, nearly 6 years after the surface mission began, the AEGIS software system allowed the MER Opportunity rover to autonomously detect science targets of specified parameters during long traverses, and target them with science instruments [21]. The system allowed greater mission science return both by reducing the amount of image data sent to Earth to be inspected for targets, and consequently, by allowing faster progress on long traverses through areas with few such targets.

AEGIS has shown that sophisticated techniques for science autonomy can help to increase mission science return and help to relieve the constraints of communication limitations. The AEGIS system is now being adapted for the MSL rover for use in instrument targeting [22], and future missions, especially those with highly capable science payloads, could benefit from similar strategies. For surface missions to solid bodies in the solar system, the targets to be discovered and characterized by such autonomous systems will most commonly be of a geological nature, supporting investigations in geology, geochemistry, and astrobiology [23]. Such future systems must function while fitting into the scientific process of exploring and characterizing a geological setting as executed in robotic fieldwork on planetary surfaces.

4.2 Exploring a geological setting

Regardless of the specific investigation objectives, surface exploration will generally involve delineating and characterizing a surface composed of connected masses of different rock types. The layout of these *geological units* tells the story of their formation and evolution - be it from sedimentary layers forming progressively one on top of another, igneous materials intruding between masses of older rock, or violent impact processes creating shattered and mixed materials in breccias, among many other possibilities. Whatever the process of formation, evidence is encoded in the spatial relationships of the geological units - several examples of which, for different processes at different scales, are shown in Figure 4.2.

Finding these boundaries between units, called *contacts*, is of great importance to the task of understanding a geological setting. Their density, orientation, and position can reveal much about the type of rock present, the relative age of the materials, the mechanisms of formation, and by extension, their position within larger structures. As such, spatial relationships between different types of geological material are essential to understanding the formation and evolution of an environment. This holds true across all scales - from kilometre-sized (and larger) provinces of material, to microscopic structures. In fact, an investigation of a new environment best proceeds at a succession of decreasing scales [24], mapping out the distribution of units at each scale before choosing targets to move in for a more detailed view at a finer scale, recursively. This follows the field geological practice of beginning with maps and remotely-sensed imagery, conducting field reconnaissance, and choosing first sites, then outcrops, then samples, before moving to microscopic analysis. In the case of a rover mission, this cascade of mapping geological units at finer scales ends with instrument placement on chosen targets, perhaps including sampling operations.



(a) 100-metre cliffs cut from the central uplift of the Tunnunik impact structure in the Northwest Territories, Canada, show sedimentary layers of different materials tilted by the impact.



(b) A roughly 10 m wide face of an outcrop in the Mojave Desert, California, shows a sharp contact between volcanic units - a lahar deposit below, and a massive basalt above.



(c) In Gale Crater, Mars, the 'Link' conglomerate is visibly distinct from the surrounding material, and itself contains numerous clasts of various compositions. The field of view is about 0.25 m wide. Image credit: NASA/JPL-Caltech/MSSS.



(d) A hand sample of impact breccia from the Haughton impact structure in Nunavut, Canada shows embedded cm- and mm-sized clasts of various compositions. The field of view is about 10 cm wide.

Figure 4.2: Several examples of visibly expressed spatial relationships between distinct, but adjacent geological materials, at a variety of scales.

4.3 Completing the picture with chemistry and composition

The application of chemical and mineralogical instruments is an important part of the investigation. Vision is often sufficient to reveal spatial relationships. But vision can only give partial information as to the composition of rocks, because of their great variety, the variability in the appearance of a given rock type, and the numerous effects, such as weathering, which can alter the appearance of a rock. In terrestrial field geology, samples from each unit are often taken for analysis in a laboratory; in the planetary setting, the analysis must generally be done at the field site. Miniaturized versions of many common laboratory tools used by geologists have been developed for planetary missions. They can be grouped, operationally, into three categories: remote-sensing instruments, contact science instruments, and sample-analysis instruments.

4.3.1 Remote-sensing instruments

Remote-sensing instruments gather data on targets at some distance from the rover, typically with a range limit of metres to kilometres. Cameras are common, and can often be targeted blindly unless detailed range is needed for focusing, or particular targets are desired and the field of view is small. Stand-off spectrometers may require detailed information for targeting, such as range to the target and fine pointing instructions. The laser-induced breakdown spectrometer of MSL's ChemCam instrument, for example, analyzes spots with a diameter of 350 to 550 μ m [25], so targeting it calls for a decision about which spot(s) on an outcrop are to be analyzed.

4.3.2 Contact science instruments

Contact science instruments require placement against the surface of a target, or, sometimes, in very close proximity to it. This category includes contact chemistry instruments - all four Mars rovers to date have carried a version of an Alpha Particle X-ray Spectrometer (APXS). [26] [27] [28] It could also include close-range high resolution imagers which must be placed in close

proximity to desired portions of an outcrop, such as MSL's Mars Hand Lens Imager (MAHLI) [29], or sampling systems such as drills or scoops (which MSL also carries [30]). Deploying such instruments requires identifying high-value science targets within an outcrop. These must also suit relevant engineering limitations such as reachability, flatness, and orientation. Such detailed information often takes time to acquire, and may require several cycles of passing information through operators on Earth. This means that contact science observations are currently costly in time and other resources.

4.3.3 Sample-analysis instruments

Sample-analysis instruments conduct their observations on a portion of sample material, which must first be acquired by a contact tool. They might include various chemistry experiments and spectrometers, such as on the Viking [31] and Phoenix ([32], [33]) landers and the MSL rover ([34], [35]). This implies prerequisite contact science work, at least for the sample acquisition system, but likely also for instruments to characterize and select the sampling sites. Significant mission resources may be expended for such sample analyses, in fact, the instrument is often capable of executing only a limited number of them, so careful selection of sampling sites and of samples is generally needed. This implies significant work by other science instruments first, and generally many steps of ground-in-the-loop decision-making and interpretation ahead of the analysis, making sample-analysis observations significant events which depend on appropriate identification and selection of science targets for sampling.

4.3.4 A progressive investigation sequence and the place for autonomy

This division of instruments implies a hierarchy of investigation tools, in increasing scale of resources expended, with the more resource-intensive instruments generally dependent on preceding work by those which are less demanding. This hierarchy mirrors, and parallels, the cascading levels of detail and scale inherent in the mapping and imaging aspect of the work. The two streams of tasks are, in fact, mutually complementary, with chemical and compositional

Step	Task
1	Acquire imagery of the region surrounding the rover
2	Identify outcrops in acquired images
3	Rank and select outcrops
4	Map the selected outcrop by recognizing geological units and their boundaries
5	Use map to identify remote-sensing targets in the outcrop
6	Take remote-sensing measurements to confirm or refine the outcrop map
7	If desired, identify targets in the outcrop for contact science observations
8	Conduct contact science to improve the characterization of the units
9	If desired, identify targets in the outcrop for sampling
10	Conduct sampling operation
11	Conduct sample-analysis science operations

Table 4.1: Simplified investigation sequence for exploring a geological environment

data aiding the interpretation of the imagery, and vice versa. They thus fit into a single, iterative investigation process whereby an environment is explored and analyzed at finer scales and increasing detail.

A notional description of the portion of this investigation which occurs during a rover traverse on a planetary surface is set out in Table 4.1. In practice, the tactical steps described here fit into the mission-scale strategy of the investigation, and will be repeated at each site of interest explored. Moreover, individual steps here described may be iterated several times to gather the data or prepare the conditions needed to proceed to later steps, and the process can be interrupted at any point if the present investigation site is judged unsuitable for expending the resources needed at those later steps.

The process in Table 4.1 is very generalized; the details will depend on the instrument suite available, the science questions being addressed, and the overall mission strategy. But such an approach of cascading scales and detail is very generally applicable, and mirrors the approach used in terrestrial field geology [24]. As presently implemented in planetary surface missions, this sequence, from start to finish, requires multiple ground-in-the-loop steps, each of which imply data transmission to Earth for analysis and assessment, and time delays for

that assessment to occur. If any of these steps can be achieved even semi-autonomously, the number of command cycles needed to complete this process could be reduced (saving time on a limited-duration mission) as could the amount of data sent to Earth (relieving constrained data budgets).

There are many points in this investigation sequence where autonomy could make a useful difference. The present work focuses on step #4 – visual mapping of geological units at the outcrop scale, and the potential utility of such a computer vision capability which is currently in development.

4.4 The visual segmentation algorithm

Recent work has developed a computer vision algorithm able to segment images of rock outcrops along geological units. The work was presented in [36], with the technical underpinnings developed in detail in [37] (reproduced in this thesis as Chapter 3). While at least one other project has attempted to address a similar problem using information from visual texture in the image [23], the present work represents, to our knowledge, the first attempt towards identifying geological contacts in a single image by unsupervised vector clustering, as well as the first to use Mahalanobis distance metric learning for geological segmentation. The technique is based on the premise that in a scene containing a visible geological contact, the geological units on each side of the contact will visibly differ from each other simultaneously in several distinguishing characteristics — perhaps colour, albedo, or texture, for example.

The ability of this algorithm to be trained on a diversity of scenes, and to thereafter map new outcrops with novel appearance or composition, makes it a potentially valuable tool for a robotic mission exploring a planetary surface. Rovers traveling long distances could use a similar approach to draft maps of outcrops and respond appropriately before these features are seen by operators on Earth. The following section describes several operational scenarios in which this kind of visual mapping system could improve the time and/or data efficiency of a robotic surface investigation.

4.5 Autonomy scenarios enabled by visual outcrop mapping

Autonomous segmentation of geological scenes in a scientifically meaningful way provides several ways to enhance mission science yield.

4.5.1 The map as data product

On its own, the generated map of geological units is a useful data product. The arrangement of the units and the nature of their boundaries provide relevant diagnostic information, and for a sufficiently uniform surface or environment, some operations scenarios could allow the map, or some reduced description of it, to be transmitted to Earth, rather than transmitting a full suite of photographs for each outcrop.

Even if implemented as ground software, the system could be used to analyze returned images, as a tool for scientists tasked with analyzing large data sets and inspecting images for interesting features.

4.5.2 Regional mapping

What applies for a single outcrop also applies at the regional scale when considering the outcrops in an area. Detection of the regional distribution of certain geological units, or of the presence of veins or contacts in certain areas, for example, can inform larger-scale mapping of a region, as inferred from the windows into the subsurface that the outcrops provide. This could be done on Earth using the software system as a tool, or potentially with a degree of autonomy by a rover itself. For example, if one type material consistently occurs as clasts or veins in outcrops, but after some distance on a traverse begins to appear in large, contiguous units, this may indicate that a significant boundary in the regional geology has been crossed, which may warrant certain action by the rover or the mission science team.

4.5.3 Data triage

While every new part of an unexplored environment is potentially interesting, exhaustive imaging is not often the central goal, nor permitted by data constraints. Outcrop maps, and in general, maps of the terrain in the working environment, could inform decisions about which data to send to Earth. For example, in a sedimentary environment, the same sequence of materials will generally repeat itself at many distinct outcrops over a large area. New images of the same sequence may not be of great scientific interest if it has already been well-studied. But an outcrop where this pattern is changed may indicate any of several disruptive events that affected the sedimentary beds, or a previously unrecognized complication in the sedimentary history, such as an unconformity.

4.5.4 Discovery-driven activities

Criteria from the map morphology might be used to drive rover decisions - veins or clasts might be important, or the detection of sharp linear contacts might indicate a fault or other feature making for a valuable investigation site. Operators could use science goals to define criteria for novelty in the constituent units of the map or spatial relationships. For a rover on a long traverse to a distant destination, or tasked with surveying a wide area, such morphological cues might be used to interrupt the traverse, collect additional imagery, and wait. Such an interruption might even allow the rover itself to decide whether and how to react to such discoveries, and perform instrument operations in line with defined criteria and conditions.

4.5.5 Targeting instruments

Instrument operations, whether autonomously triggered or initiated by operators on Earth, could be guided by the outcrop-scale map of geological materials. A stand-off spectrometer might be targeted to several points in each identified unit, to ascertain its composition and confirm its homogeneity. The results of those observations, if processed on-board, might even

be fed back into the algorithm for mapping the units, if they show a need to reconsider the number of units present.

A stand-off instrument could also be used to take a raster series of observations across detected geological contacts, or across veins, clasts, or other small-scale features, characterising them and directly comparing immediately adjacent materials, while simultaneously confirming the position of the detected boundary.

4.5.6 Enabling contact science

Having mapped an outcrop (and perhaps also studied it with remote-sensing instruments), the outcrop segmentation could be used to identify areas of suitably homogeneous material which are sufficiently large to accommodate a contact instrument. Together with 3D shape and range information from onboard sensors, these candidate targets could also be assessed for safety and suitability for the instrument placement. Where it is not practical to target the same part of the outcrop with multiple contact or remote instruments, the segmentation could be used to identify separate regions of the same material in the outcrop, suitable to each instrument.

The further step of using these identified targets autonomously by placing contact instruments on the outcrop in response to autonomous identification of scientific value, safety, and suitability, is a very ambitious proposition with significant risks, and would require an extremely robust system worthy of great confidence in its reliability. Such a step may not even be necessary or desired, since by the final stages in fine-scale science investigation, the science team employing the robotic system will be very interested in understanding the environment for themselves in great detail, and in guiding the investigation now that the autonomous system has found targets worth their interest. As well, contact science operations entail both greater risks to the robotic systems and instruments, and greater consumption of time and resources, so will merit a manual approval step for the foreseeable future.

4.5.7 Strategic use to improve mission throughput

Even the most conservative autonomy scenarios could make valuable use of visual geological segmentation. Their best role in the process of Table 4.1 will depend on the mission architecture, instrument suite, scientific goals, and exploration strategy. They might best be implemented where they can reduce data volumes, improve the value of the data returned, or save time by reducing the number of ground-in-the-loop cycles needed to achieve a particular task, or more broadly, to achieve the mission goals. This could also imply a division in time - the system might be used in certain environments, during certain phases of the mission, or during certain kinds of traverses - for example long traverses over mostly familiar terrain, or survey operations aiming to map out the extent and position of materials of interest. Regardless of the specific application, a reliable strategy for autonomous geologic segmentations in images is a powerful and flexible tool for autonomous rover geology.

4.6 Conclusion

Computer vision techniques are progressing with respect to interpretation of natural scenes, and a tool has recently been developed which is capable of segmenting images of geological scenes such as rock outcrops. The system is able to be trained to recognize a variety of types of geological materials, and could be adapted to a variety of tasks. It could also be repeated at finer scales as a rover approaches a target, fitting into the exploration process at many stages. Such visual mapping is a prerequisite to many tasks in geology and surface exploration, and a variety of scenarios exist where a flight implementation of such a tool could improve the efficiency in data and time, as well as the quality of scientific data returned, of robotic exploration missions. These techniques can be implemented strategically to best make use of the capabilities of the robotic system and its operators on Earth, and to mirror in their execution the practice of terrestrial field geology, adapted to the planetary setting.

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Chapter 5

Observations of Wind Direction by Automated Analysis of Images from Mars and the MSL rover

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5.1 Introduction

5.1.1 Context

The first decade of the twenty-first century has seen an unprecedented flourishing in the robotic exploration of the solar system. At present, spacecraft missions are underway to the Earth's moon, all but the outermost planets, and several minor bodies across all regions of the system. The missions have produced tremendous amounts of data from the instruments they carry, allowing new discoveries that have greatly affected our understanding of the Earth's neighborhood. This large data volume presents challenges for mission scientists and engineers; however, as radio links over interplanetary distances limit the rate at which the data can be returned to Earth. In fact, the bottleneck of the communications system is a key driver for the entire mission architecture used in planetary missions, from the selection of instruments and design of spacecraft subsystems to the scheduling of observations and the choice of landing sites and targets of investigation.

Even after the data is delivered to Earth, significant challenges remain in making the best use of it. A single mission can gather data for many years, and several missions to the same or similar target bodies can produce great volumes of data that are difficult to analyze as a whole. Significant human effort and time is needed, ans not always available, to thoroughly investigate incoming data, and new discoveries are often found by reviewing old data and comparing it with newer acquisitions.

New data processing techniques can present a way of addressing both problems — data reduction aboard the spacecraft and interpretation on Earth. For data from imaging systems, this can take the form of autonomous image-processing techniques, which allow computer systems to autonomously identify features of interest in images.

5.1.2 Present work

The present work aims to develop automated image-processing techniques for atmospheric studies. In particular, the aim is to develop a system allowing the automated extraction of wind information from imagery of clouds taken by surface-based instruments. The efforts described in this paper present a technique for such analysis to be performed on data already returned to Earth. This allows faster and more accurate determination of winds at the cloud level than by manual inspection, and can provide a way of obtaining wind information when no dedicated anemometry sensor is available.

5.1.3 Contents

Following this introductory section, the motivation for this work, in support of planetary atmospheric science and autonomous computer vision, is described in section 5.2. Section 5.3 describes the computational approach used. Section 5.4 describes the present results of the development; while Section 5.5 describes the planned application and utility to the Mars Science Laboratory mission currently operating on the Martian surface. Section 5.6 describes anticipated future developments.

5.2 Motivation

5.2.1 Atmospheric science

For planetary bodies with atmospheres, understanding the global circulation and local weather in the atmosphere is of particular interest, both on its own and for its use in understanding surface processes. In the case of Mars, eolian (wind-driven) processes are thought to be of great importance in influencing the erosion of geological features, and the formation and evolution of such features as dunes.

Clouds are known to exist in the Martian atmosphere, and their role in transporting moisture is of great interest. The motion of moisture-bearing clouds, and their interaction with the solid surface, has implications for the nature and preservation of ancient features which might be investigated by surface missions. In particular, the record of biomarkers which might exist from ancient Martian life could be heavily affected by surface interaction with moisture.

5.2.2 Operational efficiency

An understanding of the behavior of Martian clouds, and the wind patterns both near the surface and at the condensation level (where the clouds form) is of interest both for atmospheric science and astrobiology of Mars. The value of an automated system is the great savings in time and improvement in precision afforded by automated analysis over manual inspection of images. In the long term, should such an automated system evolve into flight software for a landed mission, a great reduction in the data budget for the wind investigation could be realized. Sequences of images could be replaced by short strings of data describing the calculated wind, giving the same information for much reduced data volume.
5.3 Approach

5.3.1 Background

Clouds have long been difficult targets for automated image processing because of their highly variable shape and texture, continuously changing appearance, and irregular boundaries [1]. Some work has nonetheless been conducted in attempting to track their position and extent by analysis of photographs for climate studies [2]. The motions of clouds are also a useful proxy for wind speed and direction [3], however, and this has led to efforts in cloud tracking in cases where other means of measuring wind are not available, such as in the atmospheres of Venus [4] and Jupiter [5]. Such approaches have also seen extensive use for the observation of large-scale atmospheric motions on Earth, by imaging from meteorological satellites. These efforts have often applied template-matching methods [6], [7] to account for the short lifetime of fine-scale features in cloud imagery, and have become sufficiently accurate to be used for operational meteorology [8]. Efforts to apply more advanced fine-feature recognition techniques, such as correlating SIFT features between images, have found difficulty in identifying appropriate, persistent cloud features [9] between images, even while showing promise for further development.

Moores *et al.* [10] showed a method for studying winds at the cloud height when orbital observations were not available. This work used the Surface Stereo Imager (SSI) camera on the Phoenix lander to capture sequences of images of clouds above the landing site. By visual investigation of the sequences, cloud features could be identified and their motion estimated, giving a way of determining wind direction at the time of the observation. The image analysis in this case was entirely manual, with no automated cloud-tracking techniques applied.

5.3.2 Technique

The wind analysis begins with the acquisition of a sequence of images of the sky, taken from a ground-based instrument. These images are taken with known camera orientation, preferably

with the camera axis aimed at local zenith. The images are taken at a known, and nominally regular, temporal spacing. The original Phoenix dataset of Moores *et al.* used a spacing of approximately 60 s and obtained sequences of 10 - 16 images each [10].

A given pair of images, for example image n and image n + 1 of the sequence, are selected for analysis. A subframe of image n + 1 is extracted, corresponding to the central rectangular region having one quarter the area and half the extent in each dimension as the original image (the central quadrant). An automated algorithm computes the normalized cross-correlation of this subframe and the full frame of image n.

This produces a pixelwise map of correlation coefficients corresponding to the mathematical correlation of all pixels of the subframe with those of the preceding image, for every position at which the subframe can be fully overlain on image n. Higher correlation values correspond to greater similarity between the set of pixels in the subframe and those in the overlain region of image n.

The pixel position with the highest correlation score is taken as the reference point for the cloud motion, and the vector, in pixel space, which would translate this point to the image center is taken as the wind vector.

Using the central quadrant provides a large sample area on which to base the correlation calculation, while allowing significant room in the pixel space for linear translation of the subframe to find the point of highest correlation. Starting from the centre, in particular, allows for translations in all directions, since no information about the wind direction relative to the camera frame is assumed.

This area-based correlation approach has the benefit of comparing relatively large-scale features and regions in the image. For clouds, which continuously visibly deform, form, and dissipate on timescales of seconds at all spatial scales, this approach can help to match areas in one frame which, though changed, retain some resemblance to their earlier form.

5.4 Current results

5.4.1 Performance for terrestrial clouds

The algorithm has been tested with photographic sequences of terrestrial clouds, and with the same images from the Phoenix mission used by Moores *et al.* [10].

For terrestrial clouds, the images were acquired at Victoria Island in Northern Canada on 5, 7, 8, 9, and 10 July 2012. Sets of images were captured with individual samples at a temporal spacing of 12 s. The sample data tested to date include examples of clouds with several morphologies and degree of coverage of the image frame, including cumuli-, cirro- and stratiform clouds at a variety of altitudes.

In our analysis, we ran the algorithm over pairs of images of the sky spaced by 12k s, for (where data was available) k = 1, 2, ..., 10. Our primary interest in analyzing these images was to determine wind direction in the image plane. Determination of wind velocity requires an estimate of cloud height as well as an image plane vector. Cloud height can be inferred using lidar [11] or from meteorological data (temperature and humidity) if necessary, but wind vector direction provides much information of interest to planetary scientists seeking to understand prevailing weather conditions especially with regard to eolian processes which influence surface morphology [12], particulate deposition [13], and climate modeling [14].

To facilitate the correlation between image-plane motions and wind direction at the observing site in geographical co-ordinates, the test imagery was acquired with the camera bore pointed at zenith. Seen from directly below, the cloud motions are assumed to be horizontal, in a plane parallel to the ground.

Over the five days when terrestrial data were collected, two days (7 and 8 July) had visually opaque cumuliform clouds and steady wind flow (see Figure 5.1 and Figure 5.2 for a typical example). On 5 July, the sky showed wispy cirroform clouds with very slow drift (see Figure 5.3). On July 9, the sky was partially overcast (see Figure 5.4) with little or no visible wind flow. Finally, on July 10 the sky was a uniform overcast.



Figure 5.1: Example of cloud imagery sequence for terrestrial clouds. Here, four images from test data sequence of 7 July 2012 are shown, spanning a total of 132 s. The first and second frames shown here are used in the preparation of Figure 5.2



Figure 5.2: Example of wind vector calculation for terrestrial clouds. The inset is the central quadrant from an image in terrestrial test data sequence of 7 July 2012. It is overlain at the point of highest correlation on another image acquired 48 s earlier. The translation which returns that inset to the image center represents the wind vector.



Figure 5.3: Example of cirroform clouds from the Canadian arctic (5 July, 2012 image set).



Figure 5.4: Example of rapidly evolving partial overcast (broken) cloud layer from the Canadian arctic (9 July, 2012 image set). These four frames are acquired at 12 s intervals; the first is enlarged above. True wind direction and speed (measured by the photographer) was, within 10%, the same as on the 7 July sequence shown in Fig. 1, but with these clouds at much lower altitude. Rapid evolution and motion of these very low-altitude clouds prevented detection of trackable features from one frame to the next on 12 s intervals.

Table 5.1:	Comparison of computed wind direction to values from human inspection. Mean result	of
	computed wind direction, over all pairs, and standard deviation of computed result, compar	ed
	to visual inspection of the sequence by a human.	

Date	Mean	Standard	Wind direction	Human
	computed	deviation	human	uncertainty
	wind	of computed	inspection	
	direction	wind direction		
5 July	342°	0.59	340	±15°
7 July	248°	0.13	240	±15°
8 July	98°	0.10	90	±15°
9 July	79°	1.41	Nil	N/A
10 July	81°	1.54	Nil	N/A

In all cases with visible wind motion, the algorithm was able to calculate wind vectors between pairs of images. The computed vectors agree with those obtained from visual inspection of the images by a human (see Table 5.1). Figure 5.1 shows an example of a cloud sequence used for testing. Figure 5.2 illustrates the correlation result.

Statistical analysis of over 8800 image pairs suggests that, for a given set of images, comparison of multiple pairs of frames can yield a more reliable estimate of the wind vector. As mentioned above, we ran the algorithm over sets of image pairs separated by 12, 24, ..., 120 s. The confidence yielded by the auto-correlation algorithm decays monotonically with temporal spacing of the image pairs (see Figure 5.5). This effect is predictable. Images of the same cloud, separated in time, will tend to differ because of constantly changing small details of the clouds. The standard deviation of these values is also presented, in Figure 5.6. They remain low across the range of image intervals, suggesting that consistency of results across pairs of images could be used as a test for successful wind calculation, even more than a threshold on the confidence values.

Indeed, in ambiguous cases, such as clear sky or an overcast with few features, the confidence on any individual match could be very high (an empty blue sky correlates very well with itself) — but the directions would be inconsistent, or often null (as was found for the 10 July



Figure 5.5: Mean of correlation confidence scores for image pairs, as a function of time between image acquisitions. Equipment failure prevented a full-length data collection on 5 July, restricting the statistical analysis to image spacings of 48 s and less.



Figure 5.6: Standard deviation of wind direction computed from image pairs, as a function of time between image acquisitions.



Figure 5.7: Standard deviation of wind direction values for the visually-ambiguous case of 9 July 2012. As the mean values vary greatly, they also show large and inconsistent spread.

overcast case, and in tests with clear-sky images).

An example of such an ambiguous case, where clouds are nonetheless present, is the set of terrestrial images from 9 July 2012, in which conditions led to an absence of noticeable wind drift even as the clouds changed shape and form continually (see 5.4). Even by visual inspection of the images, it is rarely possible to infer a motion between adjacent frames. This set did not allow consistent wind vectors to be calculated, as would be predicted. Figures 5.7 and 5.8 show the results of calculations on this set. For any chosen imaging interval, the standard deviation of the computed result across all pairs is large, meaning the results are inconsistent. Varying over the possible imaging intervals, the mean result varies significantly, and with no clear trend.



Figure 5.8: Mean wind direction values, in radians from the origin (image frame up). For this case of visually-ambiguous cloud motion, the direction values vary greatly, and no trend emerges.

Where visual information is not available, then, the algorithm fails to produce consistent results. Where wind drift is apparent to a human observer, however, it gives consistent results across sets of images. This consistency can thus be used as a criterion for detecting correct wind estimations. As well, the consistent results, with standard deviations corresponding to uncertainties of 5° or less in the wind direction, allow much finer estimation of the wind direction than with visual inspection of the images by a human. In the technique used by Moores *et al.*, for example, directions were specified to the nearest 22.5° (choosing octants) [10].

5.4.2 Application to imagery from the Phoenix mission

For Phoenix sequences in which clouds are present and have sufficient visual contrast to be visible to a human observer, the algorithm has successfully calculated cloud motion vectors. As for the terrestrial datasets, the vectors are consistent across image sequences. Due to the long inter-image time (approximately 60 s), the algorithm does not work with images separated by more than two positions in the sequence (i.e., image *n* can be used with image n + 1 or n + 2, but no further), since in most cases the features move outside the frame after one or two image intervals.

Figure 5.9 shows an example of a cloud sequence used for testing. Figure 5.10 illustrates the correlation result. Optically thick clouds have been identified in eight image sequences from the supra-horizon images from the Phoenix mission, as identified in Table 5.2. In each case, using the standard deviation test proposed using the terrestrial data, the algorithm correctly identifies a wind vector.

Unlike the terrestrial datasets, these images were taken at various elevations above the horizon, and so rectifying image-plane motions to local geographic directions is more challenging (though not impossible, given knowledge of the camera parameters and pointing). However, the goal of this test is to demonstrate stability of the algorithm and applicability to the cloud conditions observed on Mars, and the lower-resolution, longer-interval imaging of the Phoenix instrument compared to the terrestrial test case. A successful computation of Phoenix wind vec-



Figure 5.9: Example of cloud imagery sequence for Martian clouds. Here, four images from the test data sequence of Phoenix sol 128 (starting with spacecraft clock 907579500) are shown, spanning a total of 207 s. The first and second frames from left were used in the preparation of Figure 5.10. These images have been processed for contrast enhancement.



Figure 5.10: Example of wind vector calculation for Martian clouds. The inset is the central quadrant is from image 2 in the data sequence from Phoenix sol 128. It is overlain at the point of highest correlation on image 1 from the same sequence. The translation which returns that inset to the image center represents the wind vector.

Sol	Time reference	Std. dev.	
	(Spacecraft		
	clock)		
94	904563738	0.0357	
98	904915098	0.0288	
128	907574643	0.0170	
128	907579500	0.0277	
131	907854773	0.0194	
132	907920238	0.0082	
132	907927759	0.0595	
148	909349860	0.0527	

Table 5.2: Algorithm results for Phoenix supra-horizon images.

tors which match the visual inspection of the scene, and are consistent across the sequence (low standard deviation) would be suggestive of successful results with the MSL mission, where zenith camera pointing and a more capable imager are available.

Optically thick clouds are not often present in the Phoenix image sequences. In many cases only dust billows are available, and significant pre-filtering is required to make these visually distinct. These dust billows show a high rate of change in visual appearance during the long interval between images (typically 60 s). There is also significant noise associated with expanding the narrow band of the visual brightness associated with the dust in an effort to increase the contrast. For these reasons, the algorithm has not yet been successfully used for sequences where only dust, but no clouds are present. The development of a suitable filtering technique is on-going, though it is anticipated that the problem can be greatly reduced by shorter imaging intervals (which is not possible for the already-acquired Phoenix data). Figure 5.11 shows an example of such data.

5.4.3 Limitations

The cross-correlation technique depends on the presence of visually distinct objects in the scene, which are persistent across the time interval between the acquisition of the first and



Figure 5.11: Example of cloud imagery sequence for Martian airborne dust. Here, three images from the test data sequence of Phoenix sol 26 (starting with spacecraft clock 898525288) are shown, spanning a total of 202 s. These images have been processed for contrast enhancement.

second frames used, and whose appearance does not change greatly in that time. Some change in the appearance of the features is tolerated — significant evolution is apparent in the clouds on inspection of the images used, especially for long image intervals.

Scenes which do not contain such features — highly uniform fog layers, clear skies, and highly turbulent dust — do not allow the computation of a wind vector by this method. Where cloud is present, it must be of sufficient optical depth to be detected against the background by the correlator.

The technique has not yet been tested for cases where multiple layers of overhead cloud are observed. It is anticipated that the algorithm may have difficulty in many such cases.

5.5 Application to the Mars Science Laboratory (MSL) mission

The safe arrival of the MSL rover to the Martian surface in August 2012 affords a new opportunity for wind determination by this method. As was the case for Phoenix, MSL carries a wind-measuring instrument (in this case REMS [15]), which can monitor surface winds during the mission. The availability of winds aloft from the present technique will provide additional data, complementary to the surface observations, and furthering the possibility for atmospheric studies at the Gale Crater landing site.

Atmospheric studies at Gale Crater are of particular interest given the large-scale topography, which is anticipated to have a significant effect on local wind patterns and cloud formation, and the equatorial latitude, which will allow a contrast with the high-latitude measurements of Phoenix. The present technique is anticipated to be used routinely for analysis of atmospheric observations during the MSL mission. Image acquisitions are planned with zenith pointing, as with the terrestrial test imagery used to develop the algorithm, to facilitate correlation between image-plane and local geographic direction.

5.6 Future work

6.1. Statistical sampling

The image sequences originally acquired by Moores *et al.* covered a sufficient time span to produce a short animation of the cloud motion to aid in visual interpretation by humans [10]. The algorithm described in the present work, however, is capable of extracting wind information from only a single pair of images. Nonetheless, as discussed above, it is useful to sample several pairs from the same sequence, to ensure that the correlation has found a consistent wind vector. Even in cases where sufficient visual information is present to allow the computation of a wind vector, it is possible for certain frames to lack informationfor example, where sufficiently few clouds are present that some frames are cloud-free, or do not contain clouds which can be correlated to adjacent frames. A next project for the development team is to refine the algorithm by identifying a minimal number of pairwise computations required to assure consistency.

We will also expand our work to consider other image processing techniques based on interimage registration. Our preliminary results indicate that simple feature identification methods, such as the Harris corner operator, are not appropriate to the problem of registering multiple images of the same cloud. Billowing effects mean that fine-scale features do not persist sufficiently between image pairs. The auto-correlation operator overcomes this difficulty by averaging over a large area, so the effects of minor variations are damped. However, this suggests that multi-scale algorithms like SIFT, if suitably adapted, may succeed by identifying features in lower resolution scale representations of the image, where billowing effects are likely to be smoothed.

5.6.1 The dust case

As discussed in Section 4.2, it is not presently possible to extract wind vectors from image pairs showing only airborne dust, without clouds. The application shows some promise, however, and may indeed be useful on Mars, where clouds are not always present, but aerosolized dust is very common. The development of a suitable image filtering technique, and possibly additional vector-estimation methods, to handle the dust case is a pending task.

5.6.2 On-board processing

An ideal future development is the implementation of such an algorithm on board a landed spacecraft at Mars (or another planetary body with visible clouds). On-board autonomous wind computation could allow the determination of winds aloft, while only requiring the results of the computation to be transmitted to Earth at a small data cost, rather than the relatively large cost of sending sequences of images.

Such a development will require significant further characterization of this algorithm under a broad range of conditions, and a design effort for computational efficiency, balancing the computational costs of the correlation algorithm with accuracy.

Several strategies, including searching over smaller regions of the image, using smaller template sizes, the number and temporal spacing of images considered, and the imaging resolution, may all be optimized to reduce computational costs, and will be addressed as experience with the particular cloud, dust, and wind conditions at the MSL landing site are better understood, along with the performance of the imaging instruments available.

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Chapter 6

Winds Aloft Measured by Atmospheric Imaging on the Mars Science Laboratory Mission, and the Case for Onboard Autonomy

Submitted for review by the Mars Science Laboratory mission Project Science Group ahead of journal submission as R. Francis, C. Newman, J. Moores, K. McIsaac, and G. R. Osinski.

Atmospheric studies have been an important part of the integrated study of planetary science, alongside orbital mechanics, dynamics, geology, and geophysics. A planet's atmosphere is the source of its surface conditions, climate, and weather, which have important implications for surface processes studied in geology, and to the planet's past evolution. For a surface mission, the weather can influence operational plans, restrict activities during inclement conditions, and affect the lifetime and power budget of a mission, especially if it relies on solar power. For a mission focused on understanding the geology and geochemistry of the landing site and its surroundings, the prevailing winds give clues to the nature of the erosion to which the surface is exposed, the sources of materials brought by aeolian transport, and connections to distant reservoirs of material, moisture, or heat. For any surface mission, the dynamics of the winds [1] and behaviour of the upper atmosphere [2] are among the main sources of uncertainty in trajectory planning for the spacecraft as it enters and descends through an atmosphere for landing [3]. At Mars, the first surface probes gathered meteorological data [4], and monitoring

continues today from the surface [5] and from orbit [6]. New missions are in flight and in preparation, specifically to study the atmosphere [7], [8], [9].

A genuine understanding of a planet's atmosphere, including its weather and climate, requires frequent, long-term observations of several types. External imaging campaigns of several years have been achieved at Mars [6] giving information about large-scale visible features, and surface measurements are sometimes available at individual points from landers and rovers (e.g. [10], [11]). However, measurements of winds at intermediate altitudes are difficult. In the present work, we propose monitoring winds aloft during a planetary surface mission by frequent imaging of clouds above the landing site and autonomous image interpretation to compute the wind vector from the cloud motions. Such a technique could return new information about the atmospheric dynamics near the landing site, at low data cost and payload mass, giving information complementary to surface sensors and orbital imaging.

6.1 Autonomous image processing for upper-winds estimation

Tracking cloud motions to estimate winds is an established technique in planetary atmospheric studies, having been applied to images from early Venus missions [12], [13], [14]. It has mainly been applied at very broad scales, with images showing a large portion of a planet's disk. Jupiter's clouds show significant texture and detail at this scale, and their motions are useful for studying the dynamics of the atmosphere, leading to cloud-tracking studies there as well [15], [16]. Cloud-tracking is routinely used for meteorological studies of Earth, especially in imagery for geostationary spacecraft [17], [18]. As techniques have progressed, various degrees of automation have been applied to the image interpretation in each of these problems [19], [20], [21], [22].

At smaller scales, however, the use of cloud-tracking for wind estimation is less frequently practiced. On Earth, a comprehensive network of surface wind sensors is available, and other

techniques, such as regular radiosonde launches, are available to measure winds aloft. Cloudtracking has been used to support specific, cloud-related science investigations, such as efforts to understand the dynamics of cloud formation to improve climate models [23], but it is not in widespread use for routine atmospheric observation. On Mars, however, where sensors such as radiosondes are not available, and where even surface sensor data is sparse, images taken from the surface can give winds-aloft data not available by other means. This approach was used successfully on the Phoenix Mars lander mission, giving frequent measurements of wind direction from cloud-tracking in image sequences obtained with the spacecraft's Surface Stereo Imager instrument [24].

For the Mars Science Laboratory mission, a similar investigation has been undertaken using the Curiosity rover's NavCam instrument [25]. To support this work, an automated image interpretation algorithm was developed, to process image sequences returned from the rover and automatically compute the wind direction at the cloud altitude [26].

In this technique, a sequence of images are acquired with a camera pointed at zenith, with a known, nominally regular, temporal spacing. Pairs of images are analyzed, for example image n and image n+1 of the sequence. A subframe of image n+1 is extracted, representing the central portion of the image having a quarter of the total image area in pixels (the 'central quadrant'). The algorithm compares this subframe of image n+1 to all regions of image n over which it can be completely overlain, and computes the normalized cross-correlation between the subframe and each region of image n. In this way, it finds the portion of an one image in which the cloud features most closely match those in the centre of a subsequent image. The pixel-space displacement of the cloud features can then be calculated. For consistent zenith-aimed imaging, the horizontal motion of clouds in a plane parallel to the ground can be directly related to the motion in pixel space, allowing the wind direction at the cloud altitude to be determined. If the cloud altitude is known, the wind speed can also be computed.

This technique was tested for a variety of cloud morphologies on Earth, and with imagery from the Phoenix Surface Stereo Imager (SSI), with consistently accurate results. These tests

and the algorithm are detailed in [26] (included as Chapter 5 in this document).

6.2 Observations from the Mars Science Laboratory mission

The MSL science team has included a campaign of environmental and atmospheric science, including both the rover's dedicated Rover Environmental Monitoring Station (REMS) sensor suite [27], and other instruments such as the NavCam imagers [28]. The availability of wind information both at the surface (from REMS), and at altitude (from NavCam), allows a comparison between these observations.

6.2.1 Zenith imaging for cloud-tracking

The MSL mission has conducted periodic zenith imaging for wind observation, as part of a comprehensive program of atmospheric monitoring [29]. These image sequences, called 'zenith movies', are typically composed of eight frames, each taken approximately 12 seconds apart (varying slightly based on exposure requirements). They are aimed 85° above horizontal, placing the image either slightly north or south of zenith, according to the season and position of the sun in the sky. The 5° offset of the image plane from the horizontal is considered negligible (the cosine to project the image-plane vector to the horizontal plane is $cos(5^\circ) = 0.996$), and the 45° field of view of the camera has the zenith point close to its centre. The zenith movies are typically acquired every 3 - 5 sols, as operational conditions permit. Figure 6.1 shows a series of example frames, from the zenith movie acquired by MSL on sol 49.

6.2.2 **REMS wind sensor**

MSL carries a dedicated environmental sensor suite, which includes a wind sensor [27]. The REMS instrument carries out routine and frequent measurements of atmospheric properties, including wind at the surface. Unfortunately, a malfunction of the sensor after delivery to Mars has resulted in ambiguities in the measured directions, but the sensor remains able to gather



Figure 6.1: Example of MSL zenith clouds movie. Four frames from the sol 49 sequence, at intervals of 42 seconds. Image credit: NASA/JPL-Caltech

wind data, with some calibrated uncertainty. One of the two REMS sensor booms is shown in Figure 6.2.2.

6.2.3 Comparison of winds at the surface and aloft

A table of wind measurement is given in Table 6.1. This comprises all observations for which both cloud-tracked winds from NavCam, and surface-measured winds from REMS, are available within a few minutes of each other, from the first 360 sols of the mission. For NavCam, this requires that sufficiently optically-thick cloud was present to be visible moving from frame to frame, at the time of the observation. For REMS, this requires the wind sensor to have been activated, and calibrated data to have been successfully reported.

The wind direction is reported as the direction the wind is coming from, measured in degrees clockwise from north. The NavCam zenith movies have a typical duration of 2:45 minutes, while the REMS observations used for comparison are typically 5:20 minutes in duration. Uncertainties for REMS vary with azimuth, due to the nature of the instrument calibration.

An inspection of the data reveals that winds at the surface and the cloud level are frequently different. With the exception of sols 39 and 49, where the winds are (nominally) nearly aligned, the winds at the surface are in general different from those aloft. Even when the wide uncertainty in the REMS-observed direction is considered, the cloud-level winds are outside the possible range of surface winds on 4 of the 9 occasions measured.



- Figure 6.2: One of the two REMS sensor booms, as imaged by MSL's MAHLI camera on sol 526. A wind sensor element is visible on the distal portion of the boom, at image centre. Image credit: NASA/JPL-Caltech/MSSS
- **Table 6.1:** Contemporaneous NavCam and REMS wind observations from MSL sols 1-360. In all cases,
the uncertainty on NavCam wind direction is $\pm 15^{\circ}$.

Sol	Wind	Wind	REMS	Angular	NavCam	REMS
	direction	direction	wind	difference	start	start
	(Cloud	(REMS	uncertainty		LMST	LMST
	tracking)	sensor)				
24	270°	343°	$\pm 45^{\circ}$	73°	14:58	15:00
39	315°	310°	$\pm 45^{\circ}$	5°	15:41	16:00
49	315°	315°	$\pm 45^{\circ}$	0°	15:59	16:00
170	180°	247°	±90°	67°	17:52	18:00
198	180°	145°	$\pm 45^{\circ}$	35°	09:03	09:03
310	180°	095°	±90°	85°	18:42	19:00
314	210°	335°	$\pm 45^{\circ}$	125°	15:35	15:33
316	270°	030°	±30°	60°	16:38	17:00
317	030°	342°	$\pm 45^{\circ}$	132°	18:31	18:27

While the data are too sparse to infer any patterns in the local wind flows across altitudes, they are adequate to conclude that the cloud-level winds are not strongly coupled to the surface winds at the floor of Gale Crater. The winds at altitude are in general different from those at the surface, and with no consistent magnitude or orientation to this difference. These inconsistencies are not enough to understand the dynamics of the local wind flows in detail, but are sufficient to determine that surface winds are not enough for such an understanding — the upper winds are sufficiently independent of the surface winds to represent a separate process worth observing. The wind direction at the cloud height represents new and distinct information which cannot be inferred reliably from measurements at the surface alone, regardless of the precision of the surface sensor available.

6.2.4 Comparison to modeling work

Among the data presented in Table 6.1, there are four sets of measurements from mid-to-late afternoon periods within a few sols of each other. The sol 310 - 317 observations appear to have been enabled by a period of increasing frequency of cloudy conditions. In all cases, the surface winds are very different from the winds aloft; only on sol 310 is the cloud-level wind marginally within the uncertainty range of the surface wind.

Modeling the winds on Mars is an area of current research, with efforts being undertaken at global [30] and regional [31] scales, as well as with regard to flows around the particular topography of locations of interest [32].

Figure 6.3 shows a wind direction profile with altitude, as computed by such a general circulation model (GCM). This computation uses a version of the MarsWRF modeling code, which is a three-dimensional GCM parametrized for Mars' atmosphere [33]. In this case, MarsWRF is adapted to provide a 2° resolution model globally, with 5 cascading nested scales, ending with a 1.5 km resolution study region focused on the 150-km diameter Gale Crater in which MSL operates. This particular model output represents winds modeled at the season corresponding to sol 310, and the local time of day corresponding to 18:40 LMST. This is the

approximate time of the sol 310 zenith movie, and, indeed, such a climate model should be taken as suitable for similar times on nearby sols as well.

The plot in Figure 6.3 shows winds which are expected to vary significantly in azimuth over several kilometres of altitude. This can be seen on a broader scale in Figure 6.4, which shows modeled winds over a cross-section of Gale Crater, up to an altitude of 10 km.

The GCM, then, is consistent with observations that show winds aloft being very distinct from those at the surface. Though the cloud height is not known, the observations and the model are suggestive that the clouds are at a significant enough altitude to be in a distinct flow regime from the surface. Such a flow may be above the rim of Gale Crater (4-6 km high, around much of its circumference), and thus strongly independent of the internal, topographically-constrained, crater wind flow. It is not possible to confirm this with the available data, though a more extensive imaging campaign coud provide greter insight. Past observations of clouds on Mars have measured their altitudes from as high as 55 km [34] to as low as 4 km (with fog at the surface also seen) [35], making generalizations about expected height of observed clouds difficult.

The particular azimuths measured on sols 310 - 317, both at the surface and aloft, are highly varying. It is thus not possible to correlate them to the modeled winds. The day-today variability of the upper winds in particular is suggestive that, in addition to the largetimescale processes captured by the MarsWRF climate model, significant dynamic weather exists at shorter timescales. If the supposition is true that the observed clouds are part of a higher-altitude flow above the crater rim, then the zenith movies could be observing the effects of regional weather surrounding the crater. The surface winds, for their part, are subject to very local-scale topographic modification as the wind flows over surface features surrounding the rover at much finer spatial scales than the 1.5 km grid used in the model, so departure from the model predictions is to be expected. Their continual, and inconsistent, difference from the cloud-level winds, though, is evidence of the independence of the surface winds from the winds aloft. Such independent winds are also consistent with the results of the modeling over



Figure 6.3: Plot of modeled wind azimuth (degrees clockwise from north) with altitude (km) for the MSL landing site in Gale Crater, at 18:40 LMST at the Mars season corresponding to MSL sol 310 (and nearby sols). The blue band represents the variation over the 5 sol period centred on sol 310; the black curve is the mean value. Data derived from a version of the MarsWRF model with nested scales focusing on Gale Crater.



Figure 6.4: Plots of meridional wind with altitude (km) over a north-south cross-section of Gale Crater, at four points during the Martian day corresponding to sol 310. The wind magnitude is given in m/s, and the local time is given in decimal hours, Local Mars True Solar Time. Significant variations of winds with altitude are noticeable, with variation throughout the day. Data derived from a version of the MarsWRF model with nested scales focusing on Gale Crater.

the Gale Crater region .

The observations suggest, then, that the winds aloft are a distinct weather phenomenon with their own day-to-day variability, separate from the surface winds within the crater. Observations of the cloud-level winds give new information that cannot be inferred from surface wind measurements alone, and if undertaken more regularly, may provide valuable new insights into the regional weather, and constraints or confirmation for modeling work.

6.3 Limitations on cloud-tracked wind observations

While the wind observations by cloud-tracking have shown value as an otherwise-unobtainable insight into upper-level winds, there are limitations to the technique. Some of these are inherent to the practice of imaging clouds, while others are due to the realities of robotic planetary exploration. These are among the reasons for the limited amount of available observations to date, but also apply to any attempt to employ this technique.

6.3.1 Visibility of clouds

A main limit on cloud-tracked wind measurements is their reliance on the presence of clouds. Sufficiently optically thick clouds must be present to be visible in the images. Such clouds were frequently seen at the high-latitude landing site of the Phoenix mission [24], but were much less frequently observed during the first 360 sols of the MSL mission. This may partly be explained by seasonality — MSL landed during the warm part of the Martian year, when condensate clouds were less likely — but also partly by an unusually low-moisture environment in Gale Crater, compared to other similar regions of Mars [25]. In fact, the clouds which do appear at Gale Crater are often so optically thin that the automated processing algorithm is unable to discern them from the dust in the air and noise in the image – a problem also not seen on Phoenix. In these cases, manual inspection of the frames is used, though further development of the algorithm to handle these marginal cases is in progress. A contributing factor to this

is the wavelength sensitivity and signal-to-noise ratio of the MSL NavCams, which were not designed for imaging faint atmospheric features.

When clouds are infrequent, the sparsity of the upper-winds data is compounded by infrequent observations. For MSL, it has only been possible to acquire zenith movies every 3 - 5sols, typically, as opposed to the hourly wind measurements taken by REMS. A much higher frequency of observation would be required to provide a more complete understanding of the winds aloft.

6.3.2 Solar geometry

The NavCam imager used for the MSL zenith movies gives a wide, 45° field of view, which is useful for the computer vision problem of finding cloud features and matching them from frame to frame despite their temporal variation. However, this means there is a large portion of the sky near the position of the sun which must be excluded from imaging. At Gale Crater, with a latitude of 4.5° S, the sun is near zenith (that is, within or near the zenith-movie field of view) for a large portion of the day near noon. This restricts the times of day at which the zenith movies can be acquired.

6.3.3 Dynamics assumptions

Relying on cloud-tracked winds requires assuming that the clouds move with the speed and direction of the wind. For clouds in open air this is generally the case, but for clouds associated with certain phenomena, such as orographic effects, this assumption does not hold. In the case of a rover standing on a broad, mostly flat plain such as the floor of Gale Crater, the clouds can generally be assumed to be moving freely with the winds at the condensation level.

6.3.4 Wind speed ambiguity

Wind direction is valuable on its own as an indication of the overall atmopsheric flow in the region near the landing site. However, wind speed is also of interest. Unfortunately, while cloud-tracking can reliably provide the wind direction, estimating the wind speed requires a knowledge of the cloud height. Assumptions based on modeling have limitations, given the day-to-day variability of the atmosphere, and the real possiblity that the clouds are in a separate air mass at altitude, not connected by a constant or predicatable lapse rate to the surface air. Any mission implementing of automated cloud-tracking for wind estimation would benefit from also having a means of detecting cloud altitudes.

6.3.5 Scarce spacecraft resources

Operating a spacecraft on a planetary surface is a challenging and complex task, constrained by the limited supplies of power, time, and other resources involved in planning science operations. The zenith imaging campaign competes with other observations, and indeed other uses of the NavCam imagers themselves. REMS, by comparison, is able to make short, hourly observations in parallel with other activities aboard the rover.

6.3.6 Data budgets

While the zenith movies are typically aquired at low resolution and bit depth for data efficiency, they are a comparitively data-heavy way to express what amounts to a single number — the wind direction. Data budgets are a constraint for any planetary mission, and large volumes of imagery resulting from very frequent imaging could become prohibitive.

6.4 Scenarios for on-board autonomy

The zenith movies have shown themselves to have scientific value, and could, if acquired more frequently, prove to be a useful means of understanding the dynamics of the atmosphere in the region surrounding the site of a landed mission. With an automated image processing technique now available [26], cloud-tracking for upper-winds estimation is a candidate for onboard autonomous science. A suitable automated approach could allow efficient collection of this data, working within the limitations inherent to the technique.

6.4.1 Data budgets

Data budgets are a key limitation for a high-frequency investigation such as, for example, hourly sky imaging. But for the purposes of upper-winds monitoring, the information content of each zenith movie is a single number - the wind direction. Even with supporting metadata included, the data volume for routine, frequent zenith imaging could be reduced to extremely low amounts, if the movies could be automatically processed on board the landed spacecraft. For example, the zenith imaging sequences currently acquired on the MSL mission carry a data cost of 4.17 megabits, for eight frames. Were this reduced to transmitting the wind vector and metadata (generously budgeted as a kilobit) along with a single frame to show the cloud morphology, the data cost would be reduced to 0.52 megabits, a savings of over 87%. Leaving aside the images entirely and transmitting only a kilobit of wind information and metadata would be a data savings of well over 99%.

Such an autonomous observation would be subject to the same limitations as is presently the case, with the images being returned to Earth for processing. The key natural limit is the presence of clouds; sufficiently frequent imaging could best make use of the clouds when they are present, even if they are rare. The cost is additional onboard processing time and power, with corresponding savings in data budgets, and with the benefit of additional atmospheric data not obtainable by other means. The existing algorithm has a computational cost of order N^2 , and a deterministic run length. No convergence, looping, or learning algorithms are employed, so the execution is bounded in time. The time taken to complete the calculation will depend on several factors - an optimization would be made involving resolution of the images, number of frames, and frequency of the observation, given expected or observed cloud conditions and motions, and the computer capabilities available.

Efficient implementation of such a program would require the ability to detect null cases, where suitable cloud features are not present. The implemented algorithm already does this, returning a null result when it is unable to match features across frames for any reason (absence of clouds, unsuitable features, features not common to both frames).

6.4.2 Scheduling

The cloud-tracking algorithm could be run on a regular schedule, or triggered by the observation of clouds by the spacecraft's instruments. This might be achieved by visual monitoring, if, for example, a sky- (not necessarily zenith-) pointing imager, running a periodic differencing operation such as that used to detect clouds and dust devils on the MER mission [36]. Alternately, another sensor might be monitored for behaviour indicative of the presence of clouds. REMS, for example, monitors ultraviolet (UV) radiation; frequent, irregular changes in the measured UV levels might indicated clouds passing overhead.

Whatever the trigger, scheduling the cloud-tracking system to image, as far as possible, only when clouds are present would reduce the amoung of processing power and time spent finding null results, while keeping the number of measurements captured high.

6.4.3 Data triage

The basic data to be returned from each successful cloud-tracking observation is the computed wind vector, including its direction (ultimately, in the site geographic frame) and magnitude in pixel space. The image sequences used to compute this value need not be returned to Earth as part of the wind observations. However, the clouds themselves may be of scientific interest — their morphology, extent, persistence, and the correlation of these with the wind direction are all potentially valuable meteorological observations. It may be decided that one or more representative frames from each successful imaging set might be returned to Earth along with the computed wind, perhaps at a lower data priority, or with some degree of image compression.

Even greater data efficiency might be achieved by only returning such sample frames under specified conditions. These might be for example:

- particular surface or upper wind conditions
- particular environmental conditions observed at the surface
- certain times of day when the presence of cloud is unusual or more scientifically interesting
- a certain degree of cloud cover
- observed cloud morphology

or other conditions as identified by the investigators.

6.4.4 Hardware

Currently the NavCam imager on MSL is used for these observations, but the Phoenix SSI was successfully used for previous work [24]. In principle, any imager can be used, so long as it possesses sufficient signal-to-noise ratio, in an appropriate wavelength band, to contrast the clouds that are present against the sky, and sufficiently wide field of view to see the same clouds from one frame to the next, given the imaging rate.

On MSL, these investigations have successfully been accomplished as a secondary role for a camera included on the spacecraft for another primary purpose. On a future mission, a dedicated sky imager might be included, perhaps as part of an environmental monitoring suite similar to REMS. This could be a fixed, body-mounted camera (with a dust cover, if the environment calls for it), a dedicated imager mounted to an articulated mast with other science cameras, or even an all-sky imager with a sun occulter, of the kind tested on Earth by [23].

Further development of the algorithm may even allow a hardware-accelerated implementation that saves power and time, as proposed for in-situ computer vision in natural scenes by [37]. Such an implementation may further simplify the inclusion of a cloud-tracking system into an environmental monitoring suite, and allow it to run more independently of the spacecraft's main computer, easing its use as a routine, background monitoring tool.

Finally, significant value is added by the presence on the mission of a sensor capable of estimating cloud height, such as the lidar included on the Phoenix Mars lander [38]. This would allow an accurate estimation of wind speed, at the cloud height, in addition to wind direction.

6.5 Conclusions

Cloud-tracking studies are now routinely conducted on Mars surface missions, giving otherwise unobtainable insights into the wind patterns at high altitude. Such studies have potential for application wherever suitable cloud conditions are present above a surface sensor system — at Mars today, and perhaps in future on Venus and Titan, or even, in certain circumstances, on Earth. An automated image processing technique is now available which reliably tracks winds under many observed cloud conditions on Earth and Mars.

Given the limitations on the technique from both observational and operational constraints, cloud-tracking studies for winds aloft are a candidate for autonomous on-board science, with a robotic system potentially choosing when to acquire data, processing the data to obtain the relevant wind information, and choosing which data to transmit to Earth. A variety of implementation cases are possible on upcoming missions to Mars or elsewhere, from a secondary application of an existing or planned camera system, to a dedicated imager for cloud and wind studies.
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Chapter 7 Discussion and Future Work

The computer vision algorithms presented in the preceding chapters were conceived as tools to respond to needs in the current state of the art in planetary exploration, where science data acquisition and interpretation could improve the performance or rate of progress of robotic surface missions. Both have successfully operated on test data from terrestrial analogue settings, and relevant scientific data returned from robotic missions to Mars; the cloud-tracking algorithm is now in routine use to process returned data from the Mars Science Laboratory mission. Their availability leads to questions of how to use, refine, and apply them to exploration missions.

7.1 Making use of geological maps in exploration

Mapping the spatial distribution of geological materials is an essential task in field geology and planetary surface exploration. The map has value on its own — the distribution of materials is one of the main questions, and informs interpretations of the history of a locale — but it also becomes a tool for planning other operations.

To truly achieve the goal of removing a ground-in-the-loop step from the exploration process, the robotic system must not only be able to map out materials, but also react to the map by taking action. Several such scenarios for autonomous response to the geological mapping are discussed in section 4.5. Of these, instrument target identification, regional mapping, and data triage are valuable applications which could be next steps in development, and which could benefit from analogue environment field tests. Each would require significant development, including consideration of the particular strategies relevant to the robotic system overall, the instruments available, and the environment to be explored. They are discussed in general terms below.

7.1.1 Instrument targeting

Having segmented an outcrop spatially by type of rock, the next problem is choosing sites within it for investigation. Target selection depends on the scientific questions underlying the investigation, as well as on the nature of the instruments available for targeting, and the reachability of each to the outcrop. Figure 7.1 shows examples of targeting schemes that might be employed to interrogate a rock outcrop after a segmentation map has been computed. Once the map is available, and any necessary post-processing for smoothing or other adjustement has been completed, the map can be used along with distance and shape information from rover navigation sensors to target scientific instruments. These can be used to confirm or refine the segmentation, or to begin to identify the composition and character of the rocks — carrying out genuine autonomous science observations.

Depending on the environment and the nature of the investigation, the system might be directed to point a standoff spectrometer such as the MSL ChemCam [1] to sample progressively across the boundaries of the identified units, localizing the contact and characterizing the transition zone (Figure 7.1(c)). Alternately, a similar strategy could be applied to veins or other linear feautures, allowing the composition of the intruded vein material to be compared to that of its host rock (Figure 7.1(d)).

If, instead of contacts, the interest is in the overall chemistry of the rock, and its variability within or across units or regions, the system might be directed to sample throughout the spatial extent of each unit (Figure 7.1(e)), or to sample densely in small subregions (Figure 7.1(f)).

On occasion, small features within a larger host rock are of particular interest. For breccias,



(a) Rock outcrop photo



(c) Rastering across contacts



(e) Sampling variability of each unit



(g) Targeting clasts, inclusions, or small features



(b) Computed map of geological units



(d) Rastering across linear features



(f) Assessing local heterogeneity



(h) Choosing targets for contact science instruments

Figure 7.1: Examples of targeting strategies for a segmented rock outcrop, depending on the science goals and instrumentation available.

conglomerates, or sedimentary rocks with identified macroscopic inclusions, the clasts might be targeted, surveying the variety and composition of the materials for studies of their origin, modification, and similarity to the matrix that hosts them (Figure 7.1(g)).

Not all investigations can be carried out by standoff instruments; some devices, such as x-ray spectrometers [2], must be placed in contact with the rock surface to carry out their measurements. The system could be directed to identify homogeneous areas of material of sufficient size to place such contact science instruments (Figure 7.1(h)), perhaps co-ordinating them with the identified targets for standoff studies, enabling multi-modal measurements across instruments.

7.1.2 Regional mapping

The spatial distribution of geological materials is of central scientific and operational interest. This is true at the outcrop scale, but it is also true regionally. The local exposure of materials visible at each outcrop is an expression of the regional geology, in which geological units and structures such as faults extend across kilometre, or larger, scales. Regional mapping is an important part of the process of understanding an environment, and can be accomplished by combining interpretation of remote-sensed imagery of the region with synthesis of data gathered on site visits.

An example of a regional geological map is shown in Figure 7.2. Derived from remotesensed imagery giving overall landforms and their elevation, it shows a preliminary mapping of fault lines observed during initial exploratory fieldwork. These observations are made at outcrops throughout the area explored, which together can be interpreted to understand regional geology, whether for structure or composition.

A rover on a traverse through a region of interest, interpreting imagery of outcrops along its path, can become a tool for regional mapping. Information from the outcrop-scale maps generated by the segmentation algorithm can inform interpretations of the regional distribution of materials visible in the outcrops. The system could, for example, be programmed to respond to



Figure 7.2: Preliminary structural map of the Tunnunik impact structure, prepared using remotelysensed imagery and field observations from the first detailed expedition to the area, on Victoria Island, Canada. Red is high elevation, blue is low; pale blue irregular regions are lakes. White lines represent geological faults inferred from observations at outcrops visited during surface exploration. From [3].



Figure 7.3: Illustration of event-driven activities for regional mapping. The change in the character of the spatial relationships between units observed in outcrop might be a trigger for rover behaviour.

changes in the spatial relationships seen between geological units in an outcrop. Such a change might indicate a transition in the regional geology. Figure 7.3 illustrates such a case. Where one unit consistently appears as clasts within another, such as in a widely-distributed breccia unit or conglomerate, finding a large contiguous volume of the material may indicate discovery of the source material for the clasts, and the end of the regional extent of the breccia. This discovery would be of importance in producing a regional map, and the system might be programmed to react to such an event by interrupting the traverse or taking certain measurements.

7.1.3 Data triage

Another possibility for event-driven action by a rover is in data triage — ranking observations in their importance for action or for delivery to Earth. Figure 7.4 illustrates the case of a rover seeing similar materials repeatedly — in this case a consistent progression of layered rock units. Where this progression is intruded by a new material, or where the sequence of units is altered, a notable change has been detected, perhaps in alteration of the rock over its history,



Figure 7.4: Illustration of event-driven activities for data triage. The rover might prioritize certain data for transmission based on a change in observed spatial arrangement of geological units.

or in an interruption in the sequence of the layers' formation. Either novel spatial arrangement might be judged more interesting, and the system could be programmed to prioritize such observations for transmission or follow-on activities.

7.2 New visual features

The geological segmentation algorithm, as presented in Chapter 3 makes use of a visual feature space of 7 or 15 dimensions, composed of brightness, colour, and texture information. This feature space is directly extensible without modifying the algorithm. Certain examples of readily-used visual features have been identified for the next steps in testing the algorithm, and are described below. A great deal of experimental work can be done in integrating various new dimensions into the feature space, discovering which are most useful for segmentation, and determinig which sets of features are suitable to particular geological environments. This optimization of the feature space may take accuracy, speed, and computational cost as parameters, and will depend on the types of sensors to be used.



(a) Colour photo of the Ministic Lake breccia



(c) Image saturation channel



(b) Image hue channel



(d) Image brightness value channel



7.2.1 New image operations

Chapter 3 describes an implementation of the geological segmentation algorithm which uses the colour channels as stored in the JPEG image format, certain color channel differences and ratios, and certain image operations using gradients, kernels, and filterbanks (see section 3.3.2). Many options can be explored for enriching and extending this feature space.

The colour representation is JPEG red-green-blue (RGB), but could readily be transformed to the equivalent vector basis of the hue-saturation-value (HSV) system. This representation better relates to the manner in which the human vision system perceives colour [4]; its representation contains the same information as RGB, but it may prove useful to the classification by generating new channels with hue and saturation information expressed independently of each other. The example scene of Figure 2.4 is reproduced in Figure 7.5, along with its separate hue, saturation, and value channels.

7.2.2 Multispectral imagery

The experiments described in Chapter 3 use colour photographs taken at visible wavelengths. Planetary geology has made extensive use of spectroscopy in infrared (IR) and UV ranges (e.g. [5], [6], [7]), with particular wavelengths known to be sensitive to minerals of interest (e.g. [8], [9], [10]). As a result, current rovers carry multispectral cameras — the Pancams on MER [11] and the Mastcams on MSL [12] each have eight channels (though the same eight channels on every camera).

Since these cameras routinely capture images in a number of wavelength bands known to be sensitive to compositional difference of rocks, their multispectral images are potentially valuable candidates for extending the range and increasing the effectiveness of the geological segmentation algorithm. The new spectral channels could be added as additional dimensions to the feature space. Many years worth of test and training data is available from past Mars surface missions, and new data is being gathered routinely by the currently active rovers.

7.2.3 Lidar

Photographs provide views familiar to the human eye, complete with colour and albedo information that often corresponds to the chemical and physical properties of materials. However, they reduce the viewed scene, which exists in a three-dimensional world, to a two-dimensional representation. In 2D photos, it is still possible to estimate size, position, and orientation of objects, but such estimations are subject to many errors and illusions. Many misimpressions about the shape, scale, and position of viewed objects are possible, even when aided by the presence in the image of shadows, familar objects, and objects of known scale. Such uncertainties about the viewed scene can be reduced by stereo imaging, allowing the production of 3D models and anaglyphs, though these are often limited in resolution and accuracy by the difficulties and computational intensity of feature-matching and simultaneous localization and mapping (SLAM).

Lidar, from 'light detection and ranging', is an alternate modality which can be comple-

mentary to photography in geological investigations. Analogous to radar, the technique works by emitting a laser pulse, often in the infrared or visible bands, and timing the interval preceding reception of its reflection off an object of interest. The technique has been used extensively for atmospheric sounding [13], 3D modeling of objects [14], change detection in natural [15] and artificial [16] scenes, and other applications. In the form employed for geology, a sensor directly produces a 3D model of an environment by scanning a pulsed laser beam over the object or scene to be imaged. Such a system, often called a terrestrial laser scanner (TLS), produces a cloud of points corresponding to the measured positions of individual lidar reflections during the scan. Similar systems have also been deployed on aircraft for larger-scale surveys.

By directly producing a 3D model from laser time-of-flight measurements, rather than calculating one from an image pair, TLS-type lidar systems can provide very accurate and precise 3D information. As a result, this modality has seen increasing adoption in the geology and mineral resource communities [17]. It has been tested as a science instrument in geological investigations of planetary analogue environments [18], and as a visual navigation sensor for rovers [19]. Promising results in both applications have led to its investigation as a tool for planetary exploration in the context of analogue mission scenarios [20], including as an imaging tool for geological science. In these tests, lidar provided 3D information that was both useful on its own, and complementary to photographic data [21].

Reflection Intensity

In addition to the 3D position of each point, such lidar systems typically also record the intensity of the reflected light. An image produced by plotting both position and intensity data for a rock outcrop in the Haughton impact structure is shown in Figure 7.6. Several researchers have noted, in visual inspection of the data, apparent correlations between reflection intensity and the composition and physical characteristics of the target material. For example, [22] found intensity dependencies in the water content and density of rock in coastal regions, while [23] showed the potential of intensity to discriminate between snow, ice, rock, and water in lidar



Figure 7.6: Lidar image of a rock outcrop in the Haughton impact structure on Devon Island in the Canadian Arctic. Brightness at each pixel corresponds to reflection intensity of the laser beam at each point.

remote sensing of glaciers.

Such relationships led several groups to develop techniques to use lidar intensity, sometimes in combination with other information, to discriminate features of a variety of types. This found particular use for land-cover classification from airborne lidar. [24] used a combination of intensity and elevation information to identify trees and houses in scans of an urban area, while [25] investigated the intensity characteristics for a variety of land cover types. [26] improved on the work of [27] and others in identifying the ground surface in airborne lidar scans by adding intensity information to their algorithm. [28] compared the performance of pixel-wise and object-based classification techniques based on intensity, finding the objectbased approach significantly more accurate for urban land-cover applications.

Application to Geology

With lidar scanners already in use for geology and surveying, interest has developed in applying lidar-based classification efforts to geological materials. Important work has recently been done in charaterising sedimentary rocks. In these materials, intensity has shown promise in identifying composition with respect to clay content, with [29], using the technique to differentiate marls from limestones. [30] apply this clay-dependence to differentiate between sandstone and shale in both fresh and weathered surfaces, and provide a comprehensive review of intensity-based geological classification efforts to date. Others have used intensity differences in discriminating gravel from sand in stream deposits [31] and in determining the moisture content of sand [32]. Intensity has also been used to both identify and estimate the age of volcanic lava flows [33]. While [18] made use of lidar in studying outcrops in impact craters, no classification work for impactites has yet been completed.

Data processing and normalization

A key difficulty with intensity-based methods is that the reflection intensity is affected by several factors, of which geological composition is only one. Angle of incidence, surface roughness, degree of weathering, moisture content, surface contamination, atmospheric effects, and distance from the sensor all affect the observed reflectivity. Significant work in characterizing these factors has been undertaken by one research group, who have developed calibration techniques [34] and methods of characterising the sensor systems themselves [35], and used them to investigate the effects of incidence angle [36] and distance [37], adapting the radar equation to this problem. They have further presented a technique for correcting intensities recorded by lidar systems that make use of automatic gain control algorithms [38].

Additional work in estimating the distance effect, which is more complex than a simple inverse-square relationship [39], has been carried out for both empirical [40] and model-driven approaches [41]. [42] give a simple distance-based calibration algorithm.

Combining data types

Classification is also possible using the 3D shape information provided by the lidar point cloud. Brodu and Lague [43] appear to be the first to demonstrate classification in natural scenes using automated characterization of the 3D geometry of features in the point cloud. With respect to structure, rather than composition, [44] demonstrated a technique to identify and analyze fracture planes in outcrops using the point cloud, while [45] have processed lidar scans of rocks to obtain surface roughness. The potential synergies in geological classification between such 3D morphology techniques and intensity methods has yet to be explored.

The authors of [46] used lidar intensity together with co-registered colour photography to obtain multi-channel infrared and visible wavelength spectroscopic data for the Vesuvius volcanic crater in Italy, with promising results, while [47] demonstrated a technique for matching features in lidar data and photographs of complex objects. Together, these types of investigations may enable use of lidar together with photographic data for even more powerful remote sensing than enabled by either in isolation.

Addition to the feature space

Assuming suitable co-registration with the photographic imagery, lidar data could be added to extend the feature space of the geological segmentation algorithm. The intensity information might be used as an additional grayscale channel, corresponding to albedo at the laser wave-length; this image might also be subjected to any of the processing techniques used to create additional channels from the photographic data (differencing, gradients, etc.). The positional information may also prove to be of use, providing roughness information, for example, that could be meaningful in classifying geological surfaces.

7.3 New applications

The computer vision algorithm presented in Chapter 3 was developed for the purpose of improving robotic autonomy in surface exploration. The ability to segment an image of a geological scene by type of material has several other potential applications, however. Certain promising possibilities for applying the technique to new domains are discussed in the follow-



(a) Image of rock with uneven dust coating

(b) Image of rock with dust coating removed

Figure 7.7: Examples of dust-covered rocks on Mars, acquired by the MSL rover's MAHLI camera. On the left (a), a rock at the science site named Nastapoka was photographed on sol 158 of the mission, and shows uneven dust coating over its surface. On the right (b), a nearby rock at the Ekwir science site is shown as it appeared on sol 150, after use of the Dust Removal Tool. Credit for both images: NASA/JPL-Caltech/MSSS

ing sections.

7.3.1 Dust cover estimation

Surface coatings, deposited by atmospheric, fluvial, or other processes, are a common challenge in the visual inspection of rocks in outcrop. On Mars, dust coatings in particular are a perennial challenge. The dust is ubiquitous and covers most surfaces on the planet, deposited there by periodic large-scale dust storms [48]. This dust interferes with the visual and spectroscopic signals of the rocks it covers [49], making geological studies more difficult. As a result, science investigations must consider the degree of dust cover in their analysis of rocks, and the MSL rover carries a mechanical Dust Removal Tool (DRT) to prepare surfaces for study [50].

Figure 7.7 shows examples of dusty rock surfaces on Mars. The reddish dust visibly coats most surfaces in both scenes. In 7.7(a), the coverage is notably non-uniform. In 7.7(b), the underlying rock has been exposed by brushing away the dust with the MSL DRT, showing the degree to which the rock's visual appearance is altered by the dust coating.

Similarly to discriminating one type of rock from another by the visual appearance of its

surface, it may be possible to classify portions of a rock surface according to their degree of dust cover. Such a tool could be useful for identifying preferred, low-dust targets, or simply to mask out dust covered areas before attempting to analyze and classify the underlying rocks. It might also be used for ground-based data analysis by estimating the contribution of dust coatings to measurements taken of the rocks, as in [51].

7.3.2 Geological photomicrographs

Following geological field studies, the laboratory analysis of samples is a frequent next step. This often includes microscopic study, to investigate features not discernable at larger scales. The microstructure of materials can reveal a great deal about their formation and subsequent history.

Figure 7.8 shows several photomicrographs of a grain of shocked feldspar from the Mistastin Lake impact structure [52]. Linear features visible in the scene are microscopic evidence of shock effects caused by the crater-forming impact. The features are visible in several different imaging modalities - transmitted light with different polarizations, backscatter electron microscopy, and cathodoluminescence imaging.

A broader field of view of a similar material (this time from the Apollo 17 field site) is given in Figure 7.9, showing a large number of mineral grains of three types. Each has a distinct visual appearance, setting it apart from the others, but visually homogenous within each mineral type.

The segmentation algorithm might be adapted to serve at these very small scales. It could be applied to data from any of the imaging modalities, in place of its current use of colour photos, or, assuming suitable image registration, use several of them as simultaneous inputs. This could allow detection of features of interest, or mapping of the areal extent of different materials, as example applications. As such, it could be a valuable tool for quickly and accurately analyzing the mineral makeup of such samples, an important task in microstructural analysis. It might also be possible to detect the presence of the shock features visible in these images, further



(c) Backscatter electron imaging

(d) Cathodoluminscence imaging

Figure 7.8: Photomicrographs of a rock sample by various imaging modalities. Distinct grains of different materials are apparent, and linear features indicating shock effects are visible. Sample of anorthosite breccia from the Coté Creek locality of the Mistastin Lake impact structure, northern Labrador. Image from [52], used with permission.



Figure 7.9: Photomicrograph of lunar gabbro showing distinct mineral grains in plane-polarized light. Visibly distinct grains of pyroxene (greenish/brownish), plagioclase (clear/white) and ilmenite (black) are apparent, with clearly defined boundaries. Sample returned by Apollo 17 from that mission's station #9 science locality. Image provided by A. E. Pickersgill, from studies published in [52]. Used with permission.

aiding in these studies.

7.3.3 Remote-sensing imagery

The regional mapping discussed in section 7.1.2 makes use, in part, of remotely-sensed imagery from orbiting spacecraft (and, on Earth, from aircraft). That process involves visual inspection of imagery, and segmenting the scene into different terrain types based on their appearance. Figure 7.10 shows an example of this kind of imagery. In this image from the HiRISE instrument aboard the Mars Reconnaissance Orbiter (MRO), several kinds of terrain are distinguishable. An uneven, rocky plain, marked by craters and other features, dominates the lower half of the image. Above image centre, a broad band of dark sand dunes are interrupted in places by additional exposures of rock. In the upper left of the image, several different types of material are expressed, with obvious differences in brightness, corresponding to the



Figure 7.10: Orbital image of a diverse region on the surface of Mars, from the MRO HiRISE instrument. The view is inside Gale Crater, near 4.6°S, 137.4°E. As of writing, the MSL rover was situated to the right of image centre. Image credit: NASA/JPL/University of Arizona

lower reaches of Gale Crater's central mound.

A version of the geological segmentation algorithm could be trained and applied to orbital images such as these. Many of the same types of operations might be used to build the feature space, based on grayscale images such as Figure 7.10, or colour images which are also available for many areas. This kind of orbital imaging is common for missions orbiting bodies throughout the solar system, making autonomous terrain classification a tool with potentially very broad applications. But the data is not only photographic — instruments of several types are used to study the surface from orbit. Infrared and ultraviolet spectrometry, ground-penetrating radar, and sythentic aperture radar of the surface are among the datasets regularly gathered by planetary orbiters. Each could, suitably registered, become a source of one or more new dimensions in the feature space, enriching the relevance of the segmentation to the materials on the surface being mapped.

7.4 Further developments

The present work describes effective new techniques for segmenting geological scenes by making use of imagery, machine learning, and vector clustering, and proposes strategies for using this tool operationally in planetary robotics. The purpose of the work, however, and the ultimate goal, is to enable faster and more efficient robotic exploration and science investigations on planetary surfaces. Achieving this calls for implementation of these algorithms and strategies on flight missions to the planets.

The path to flight requires progressive advancement of the Technology Readiness Level (TRL) towards the point where the system is functional, reliable, and trusted for space operations. Next steps include:

• Continued testing in new geological environments, including marginal cases where imaging is difficult, to assess robustness to lighting, surface coatings, gradational bound-aries, and other image-interpretation challenges.

- Expansion, testing, and optimization of the feature space, including the various permutations described at section 7.2. This should include a study of which features collectively provide the greatest amount of task-relevant visual information for the lowest computational cost, and studies to this effect across a variety of relevant geological environments.
- Integration with a system for follow-on decision steps. This would include postprocessing of the map that might be necessary to prepare it for use in subsequent operations, and implementation of a framework to choose actions based on the map. This might include, for example, target selection in support of various science goals, data triage based on certain criteria, selection of follow-on instrument tasks, or data synthesis across maps.
- **Conduct integrated field tests** with a mobile robotics platform conducting autonomous science-driven traverse operations in a relevant analogue environment. This would demonstrate the process of using autonomously-generated outcrop maps in the loop of robotic decision making.
- Seek opportunities for flight tests on relevant platforms, including upcoming planetary missions as the technology matures through the preceding steps.

A possible test case is to conduct a large-scale investigation of images from the MER and MSL traverses and science investigation sites. Each rover has travered multiple kilometres of unpepared, previously unvisited Martian terrain, and a great deal of scientific imagery is available along the paths of all three rovers. Numerous outcrops have been imaged and studied, and the geological mapping and decisions about target selection made by the human experts planning the science investigation are known from the mission history. At each site, the system can be tested to see that it can handle the materials expressed, and (at later stages of development) choose targets of the kind selected by the real mission teams.

7.4.1 New capabilities

Enabling even more powerful autonomous science capabilities calls for two desirable, but challenging, extensions to the algorithm.

The first is a large-scale, cross-environment training, in which the MDA learning step is performed on a large number of classes in images from multiple geological environments simultaneously. So trained, the system would be able to recognize any of a large number of different types of materials, rather than the small number contained in a single setting, as is the case for the current training. While it would rarely be necessary, in practice, for a rover to handle very large numbers of geological classes simultaneously, such a system could help with novelty detection, when new materials appear along a traverse. In practical applications, however, it is important that the learned feature-space representation maximally separate those classes that are actually present and encountered, rather than compromise performance locally in the pursuit of extreme generalizability.

A related development is adjusting the clustering from *k*-means, as presently employed, to alternate approaches which attempt class number estimation. A system which could autonomously discover the number of classes present in the scene — in a way which is semantically meaningful for geology — would be capable of discovering geological units and contacts in a fully unsurpervised way. Class-number discovery is, however, a challenging task; several algorithms exist, but are generally applied to data whose properties are to a significant extent known and regular. These approaches require choosing dispersion and class threshold parameters, generally in a way that calls for an understanding of the relation of the classes to each other. Such an understanding of the visual geological feature space has yet to be obtained.

7.5 Advancing the cloud-tracking algorithm

The cloud-tracking algorithm for winds aloft estimation presented in Chapter 5 has shown consistent and reliable performance under a variety of conditions on Earth and Mars, for image

sequences of optically thick cloud traversing the scene. In cases of very optically thin cloud from MSL data, the system has been unable to obtain correlations due to the noise in the images overwhelming the visual signal. Advanced filtering techniques might increase the reach of the system to very thin clouds, but two considerations are worth noting. Firstly, there is a limit to the reach of vision systems — ultimately only cloud which is, in fact, visible can be recognized.

Secondly, for a case of on-board autonomy, the problem might be solved by reducing the image noise on the acquisition side. The present MSL zenith movies use compressed, 4-pixelbinned images in an effort to reduce data cost; were the data not to be returned to Earth, the images could be acquired at higher resolution, and possibly with a higher-performance imager configured especially for the application. The extra processing costs might well be lower than those associated with filtering or other more complex strategies devised to extract a faint motion signal from noisy images.

The path to flight for the cloud-tracking algorithm is similar to that for the geological segmenter:

- Long-time-series tests. This would comprise tests of the algorithm under long cycles of changing weather, and a comparison of the computed wind to local measurements (including information about cloud elevation, to correlate the observed with to meteorological reports). This would thoroughly validate the system under changing, variable, and diverse cloud and wind conditions.
- Integration with a system for follow-on decision steps. This test would demonstrate an ability to do event-driven data triage (and possibly acquisition), to optimize measurements acquired against processing resources on-board and data volumes transmitted.
- Seek opportunities for flight deployments. This would include assessment of the imaging system, processor, and environmental conditions, and adaptation of the system to optimize on image resolution, acquisition frequency within the sequence, observation frequency during the day, and number of frames in the sequence.

7.5.1 New capabilities

To expand the range of utility of the system, several future developments suggest themselves. A first possibility is to include information about camera pointing to allow the imager to point away from zenith. This would allow imaging near local noon, especially for low-latitude landing sites. It would require a suitable co-ordinate transformation from the observed wind vector to the horizontal plane. To avoid the out-of-plane distortion effects associated with imaging a planar field of objects (a cloud layer) at large angles from normal, it might be best to rectify the image first, then apply the correlation algorithm. The extra processing cost of this could be factored into the optimization of a flight deployment case to decide if the extra observation warrant the additional complexity and computation.

Another case to handle is that of very sparse cloud, where some frames of a sequence may contain no cloud at all, or contain clouds that do not appear in adjacent frames. Tests to date have never shown the calculation of spurious, false-positive correlation vectors from such cases (aside from featureless scenes auto-correlation to [0, 0]), but to further guard against this possibility, and to recognize the frames to be excluded, a statistical method might be applied in computing the correlation between all pairs of frames. For a sequence of tens to hundreds of seconds duration, each adjacent pair of frames (n, n+1) should return the same wind vector, and non-adjacent frames should return integer multiples of the vector (the clouds having translated e.g. twice as far from frame n to n + 2). The correct vector could thus be extracted from a sequence whose pairs give more than one computed answer by a statistical voting approach, selecting (for example) the mean of a large cluster of similar values, and rejecting outliers as arising from ill-conditioned images.

Finally, to further optimize data and processing resources, a flight system might check for clouds before beginning an imaging sequence, to save on even capturing and processing imagery when no clouds are present to track. This could be accomplished by analyzing the images for texture corresponding to cloud layers, as in the edge-detection strategy deployed already in flight to detect clouds on the MER rovers [53]. Alternately, to verify both the presence and

motion (on desired timescales) of cloud, the differencing operation used in that work to detect moving dust devils might be suitable.

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Chapter 8 Conclusion

The exploration of the solar system continues to advance. New missions are under preparation by several agencies to destinations throughout the Earth's planetary neighbourhood. Ambitious new proposals are under consideration to explore challenging new environments father than ever from Earth, both in literal distance and metaphorically, in terms of our ability to directly command them. Robotic autonomy will increasingly become important for these missions, and in some cases will be an essential enabling tool for missions that cannot be achieved without it. To a progressively greater extent, this autonomy will need to include the ability to interpret mission science data *in situ*, and use the information thereby generated to make decisions about which data to send to Earth, which new data to gather, which instruments to use, and even where to go next.

For surface missions, geology will continue to be a core focus, and mapping the spatial distribution of geological materials will remain a key task. This thesis presents an effective, adaptable, extensible technique to allow a computer vision system to segment and classify geological materials. Implemented for a flight mission, such a tool could be of great use in automating certain steps of the spatially-cascading, iteratively cyclical process of exploring a geological environment. Numerous applications are foreseen, and a great deal of opportunity exists for growth, optimization, and adaptation of the system ahead of its use on Earth, or in spaceflight.

In atmospheric science, interpretations and discoveries rely on frequent measurements over

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long periods. Observations of winds aloft are difficult to obtain on Mars, though cloud-tracking techniques have recently been demonstrated to be effective. The data cost for large numbers of imaging measurements is prohibitive, however. Here, robotic autonomy is an enabler of new science — the algorithm presented in this thesis gives the possibility of frequent, long time-series observations of winds aloft, at very efficient data cost. With continued advancements in on-board processor technology, such a technique could allow a new data stream to join the sensor suite of a future automated environmental monitoring station on a planetary surface.

New extensions of these techniques are already foreseen, and new applications will come to light requiring entirely new approaches. These new tools will be most useful and effective when they are developed by a process of engineering which is undertaken in close consultation with the science community — the end users for the data and the practitioners whose work is the motivation for these missions of exploration. These tools will be best designed and best integrated when they are executed in such as way as to fit into the processes by which planetary science is necessarily undertaken. So crafted, these new technologies can contribute to the common goal of producing systems which can enable us to better understand the universe we live in, the history and evolution of the solar system and its planets, and among them, our own Earth.

Appendix A

Example labeled images

The computer vision algorithm for segmenting geological scenes presented in Chapter 3 makes use of labeled exemplar scenes for both training machine learning component, and assessing the segmentation. Several examples are given below of images used in the testing of the algorithm, and their corresponding class labels. In each case, class labels are coded by colour, assigned pixelwise. Pixels of each labeled colour are assigned to the same class; pixels coloured black are not assigned a class label.



Figure A.1: Scene type A: Basalt blocks and sand



Figure A.2: Scene type B: Massive basalt and lahar deposit



Figure A.3: Scene type C: Layered volcanic materials



Figure A.4: Scene type D: Complex emplacement of volcanic materials



Figure A.5: Scene type E: Impact breccia (Sudbury)



Figure A.6: Scene type F: Calcium sulfate veins in dust-covered mudstone

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