Autonomous sample selection and acquisition for planetary exploration

Pugh, Stephen; Barnes, David Preston

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Autonomous sample selection and acquisition for planetary exploration

Stephen Pugh and Dave Barnes
Department of Computer Science
University of Wales Aberystwyth
Aberystwyth
UK - SY23 3DB
spp05@aber.ac.uk

Abstract

Thanks to rapid advances in planetary robotics and scientific instruments, data can now be gathered on the surface of Mars far quicker than can be successfully relayed to Earth. Pauses in activity have to be introduced, so that this additional data can be transmitted back to Earth. These pauses represent an inefficiency in the overall mission value, as value is calculated by dividing the amount of useful scientific data returned by the cost. Scientific data with little value represents a waste of valuable transmission time and thus reduces the overall cost efficiency of the mission. Pauses in activity also have to be introduced during periods when communication with Earth is impossible. A great deal of research is currently being undertaken to try to limit this time wastage through the utilization of an autonomous sample selection and acquisition system. Such a system could initially select high value science targets and then continue its exploration while only useful data is being relayed to Earth for further study, thus increasing mission value. This paper will present a review of the research currently being undertaken to aid in producing an autonomous sample selection and acquisition system for planetary exploration.

1. Introduction

The major success of the Mars Exploration Rovers (MER) has added a huge impetus to research in planetary exploration using unmanned rovers. By November 2006 the Spirit (MER) had survived 1000 Martian days (sols) (Castano et al., 2007b), during this time it has traveled more than 6850 meters (4.27 Miles). Although the Spirit rover had not been there as long by this time it had logged an astonishing 9406 meters (5.85 Miles). The MER Mission is still ongoing in the extended mission stage and promises to progress well into the future (Figure 1).

This mission has still been constrained by downlink bandwidth and although a huge area has been covered by the rover, a large proportion of it has been covered during long traverses between sites of interest. The problem with this is that it is very difficult to say from Earth what is interesting so a long traverse could be initiated to a distant sample site when a much more desirable sample lies only one meter away.

In order to search for desirable targets during a traverse, images would have to be gathered and analyzed. If every one of these image was analyzed on Earth far to much time would be wasted transferring data. If however the data could be analyzed on Mars it would be possible to examine all these images and select only the most appropriate targets to be further analyzed on Earth. This system could also be used to examine the rovers surroundings during pauses in activity that are currently introduced while data is transferred back to Earth or while the rover is out of communication range. If a valuable target is identified, further analysis can begin without immediate confirmation from Earth, thus utilizing this previously wasted time.

This type of autonomous system is not a new idea, in fact research began many years ago into plausible ways of giving robotic systems some form of self driven control. Space however offers different challenges (Muscettolay et al., 1998) and different rewards. In fact a robotic agent designed for space exploration does in itself become a scientific instrument. This raises additional questions about how the robotic system is designed, should well established robotic control paradigms be used or should the system be designed with the science that it will collect in mind.

2. Current Work

There is currently much work being done in this area of research; during this next section a brief overview of some of the work being done will be presented.

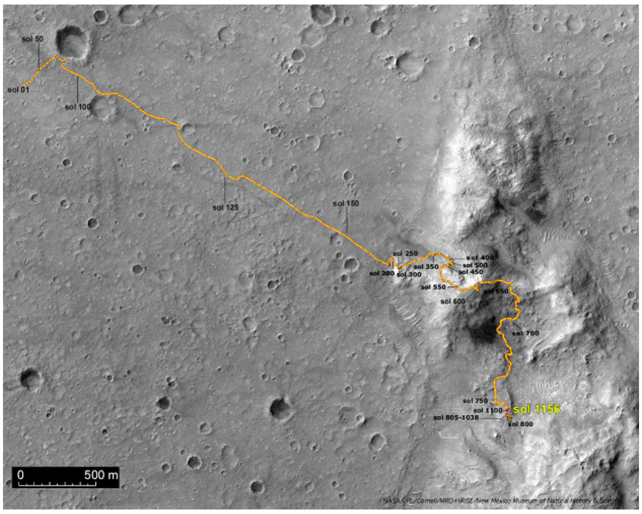

Figure 1: Map Showing the area covered by JPL Spirit Rover (Image courtesy of JPL)

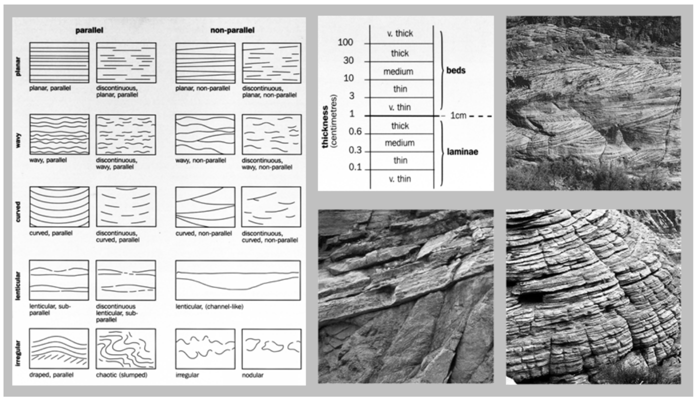

Figure 2: Example of possible structures of interest that may be found on Mars. (Pullan, 2007)

2.1 OASIS Project

The Onboard Autonomous Rover Science Investigation System (OASIS) (Castano et al., 2007b) is designed to operate onboard a rover identifying and reacting to serendipitous science opportunities. These science opportunities can include detection of dust devils, clouds and "novel rocks that the rover has not seen before". The OASIS system "analyzes data the rover gathers, and then prioritizes the data" based on established criteria (Castano et al., 2003a).

There are three main components within the OASIS system, these include:

1. Feature extraction from gathered images: Concentrates on locating rocks based on shape, texture and albedo.

2. Analyse and prioritise data: Uses the features extracted to determine scientific value of the planetary scene.

3. Plan and schedule new command sequence: Dynamically modifies the rovers current plan to accommodate new observations.

One of the main aspects of the system is the Rockster algorithm which is responsible for the identification of rocks. The algorithm initially separates the sky from the ground and then uses edge detectors and background flooding to identify potential targets.

OASIS has been built as a complete solution to the autonomous sample selection problem, they have also gone on to include a scheduling component that considers whether sufficient power and time is available to incorporate the new plan. In order to test the system on a real robotic architecture the OASIS team have integrated there software with CLARAty (Coupled Layered Architecture for Robotic Autonomy) (Volpe et al., 2001). This system provides an interface between the OASIS software modules and the rover test base allowing the integrated OASIS system to be tested. The results of the tests were impressive (Castano et al., 2005). 110 FIDO (Tunstel et al., 2002) hazcam images were used and a total of 2942 rocks were analyzed, the results were compared to targets identified be human scientists. Two scoring methods were used center matching and overlap method and the results were 89% and 87% respectively. More recent tests done in 2006 (Castano et al., 2007a) show the OASIS system identifying 36 out of a possible 40 targets over 10 runs.

There are however a number of problems not addressed by the OASIS project. Colour is not used to identify potential targets as the system uses grayscale images. Colour could potentially be a great indicator of science value and could also add some additional information regarding the target's chemistry. Also the type of targets that are being searched for, here OASIS has adhered to the classic approach of target selection that is to look for "rocks" however it can be argued that the majority of the rocks have been deposited on the surface by volcanic activity or have fallen as asteroids. Therefore samples taken from these rocks could give an unrealistic insight into Martian geology, it is therefore proposed that bedrock and exposed rock shelves should carry a much higher science priority. A recent report produced by a planetary geologist (Pullan, 2006) has indicated that structure of these potential target sites could give strong indication as to science value (See Fig 2). OASIS does not appear to cater for this type of science target.

2.2 SCAIP Project

Closed Loop Control for Autonomous Approach and Placement of Science Instruments by Planetary Rovers or SCAIP (Huntsberger et al., 2005) is a project also led

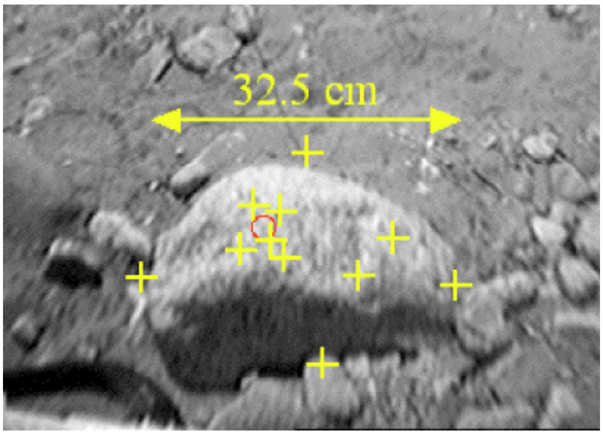

Figure 3: Instrument placement results from 11 trial runs of the prior algorithm [Huntsberger, et al., 2002, 2003], with crosses at the positions where the instrument arm made contact overlaid on the short range image used for arm trajectory planning. Instrument arm contact positions for the SCAIP effort will all lie within the 1cm radius red circle centered on the designated target. (Huntsberger et al., 2005)

by JPL to create a closed loop system system to autonomously place a scientific instrument on a foreign planetary surface. The main aim of the project is to cut down the length of time required to take a sample. This is done by reducing the level of human interaction with the rover thus reducing the amount of time required for transmission of intermediate data and control instructions.

This system, although not a complete solution focuses on the autonomy associated with the rovers command sequence. It assumes that an Earth based scientist has already specified a suitable target from downlinked images. The system will then proceed through a six stage sequence; the stages are as follows:

1. Drive to stand-off position using intrest points.
2. Hand-off goal position from Navcams to Hazcams.
3. Plan final approach path.
4. Drive to final offset position and acquire Hazcam image.
5. Arm path planning with collision checks.
6. Place instrument and acquire science data or determine a safe substitute placement goal.

The SCAIP control software gives primary importance to mission safety; if rover safety cannot be guaranteed the rover will simply stop and call Earth for help. The system shows great promise; Figure 3 shows an image overlayed with yellow crosses showing an earlier systems

Figure 4: Example rock face demonstrating lamination features (Pullan, 2007)

placement attempts, the red circle illustrates the accuracy of the SCAIP system as all trials of the system lie within this circle. This represents a significant step forward in instrument placement technology which will form an essential part of any autonomous scientific rover.

The SCAIP project itself only goes part of the way towards producing a fully functional autonomous planetary scientist. The focus on the autonomous instrument placement has enabled them to produce a robust mission ready system. Unfortunately as previously mentioned it is only part of a full system and still relies heavily on a human scientist selecting the target and producing an activity plan. The system also loses some of its efficiency if you are not able to see the exact sample point from the initial image of the sample site. The rover may have to be manually moved towards the site until the exact sample location is identified. This manual interaction although not always necessary will reduce the efficiency of the system. In the case of rocks displaying lamination or bedding features (such as those seen in Figure 4), the exact target location may not be obvious until the macro imaging stage has been reached. For example Figure 4 shows an image of an exposed rock face. if a sample was needed from the brown vein long distance targeting would be useless.

Of course not every target needs to be targeted with such fine resolution most targets can be suitably targeted from a stand off location thus utilizing the full benefits of the SCAIP system. A great deal more work however would be needed to make this system perform completely independently but as it stands it does provide a half way house and may well be a suitable intermediate step towards the use of a fully autonomous system on another planet.

2.3 Rock detection and classification

There are several projects underway focusing on this area of expertise. Carnegie Melon University have produced a paper entitled “Detection and classification of features of geologic interest” (Thompson et al., 2005) This paper presents a method that uses a probabilistic fusion of data from multiple sensor sources for onboard segmentation, detection and classification of geological properties. A belief that performance and reliability can be increased if science targets are specified in terms of examples rather than properties is presented. The method can be broken down into three steps;

1. Segmentation; potential targets are isolated from the rovers sensory input.

2. Detection; belief network is used to distinguish between target and not target areas.

3. Geological classification; the features are classified according to their physical attributes.

The segmentation step is not responsible for detecting targets but merely suggests candidate structures for further classification. The segmentation is done using a region-merging/region-growing type approach, the image is split into a grid of 5×5 pixel squares, these squares are then iteratively joined back together to form regions of uniform properties. Once all possible merges have been done every region between 20 and 50 pixels is considered a potential rock. In order to further improve the results produced by this process a simple Gaussian blur operation is applied to the image prior to its being processed.

The detection step identifies the science targets from the segmented regions by extracting a real-valued attribute vector from each candidate region and labeling it with a Bayesian belief network. A belief network is used as it solves the problem of missing data that can occur when fusing multiple sensors with varying fields of view. Several attributes of the segmented regions are considered; these include relative colour, relative colour variance, height above the ground plane, texture and intensity gradient.

Finally the geological detection step evaluates the discovered science targets and classifies them according to predefined and synthesized categories. The predefined categories are chosen at outset by an expert but the synthesized categories however come from an unsupervised clustering algorithm which runs whenever the rover collects new data.

More work has been completed by JPL. They released a paper may 2003 entitled “Techniques for onboard prioritization of science data for transmission” (Castano et al., 2003b). During this project they concentrate their efforts on the search for rocks and other science targets that are elevated above the ground plane. Detection of these objects is accomplished through use of a stereo image pair to create an elevation map of the target area. From this elevation map the ground plane can be distinguished and any protruding objects can be easily identified. These potential rock targets are then processed and properties including albedo, visual texture and shape are extracted. These extracted values are then concatenated to form a feature vector, representing the quantified properties of each rock. These Vectors are then fed into three distinct prioritization algorithms;

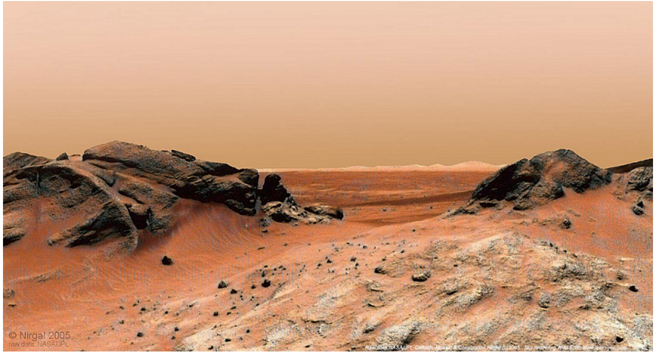

Figure 5: Image showing Martian outcrop taken on sol 694 The outcrop Comanche. (Mosaic and coloured by Nirgal (Bernhard Braun). Enhancement and sky rendering mars-geo.com. Raw image courtesy of JPL)

1. Target Signature; Target signatures are specified by identifying nominal values for each of the relevant features. An importance is then assigned to each of the features. Rocks are prioritized as a function of the weighted Euclidean distance of their extracted feature vector from the specified feature vector.

2. Novelty Detection; They have developed three methods for detecting and prioritizing novel rocks, representing the three dominant flavors of machine learning approaches to novelty detection: a distance-based method, a probability-based method, and a discriminative method. These methods for novelty detection are specifically designed with onboard constraints and large candidate feature spaces in mind.

3. Representative Target; Data is prioritized to ensure that representative rocks from each class are sampled. For each class of rocks, the most representative rock in the class are found, i.e., the single rock in any image that is closest to the mean of the set. A high priority is given to the image containing this rock. The process is complementary to novelty detection using K-means, where rocks that are farthest from the cluster means are given the highest priority.

Research has become quite advanced in the area of rock detection on a surface. However very little work has been done into land form detection and outcrop identification. The majority of the research currently being done is identifying rocks in a planar field, however as previously mentioned the majority of these rocks have been deposited in their location through some means, and therefore may not properly represent the region being sampled (For example a meteorite may contain Carbon, and may lead us to believe that Mars has Carbon). Many other rocks have been deposited on the surface through volcanic activity, these rocks also do not properly identify the region being sampled. Much better more representative samples can be retrieved from outcrops (rock formations which emerge from the ground as seen in Figure 5). These locations also provide access to rocks that could have potentially been out of rover reach prior to the event which exposed them. Their exposure may have been caused by seismic activity or through meteorite impact, however despite how they are formed they could give clues into the geologic history of the planet Mars.

In order to utilize potentially rich targets such as these an autonomous system would have to know how to identify, classify and determine which part of the outcrop will be sampled. There may be several favorable sample sites on the one outcrop so the system will have to know how to differentiate between these and what priority to give them. The safety of the rover would also be of concern and the stability of the outcrop would have to be assessed. However the detection of geologic features such as outcrops and larger rock formations should be considered of significant importance.

3. Work Being Undertaken

During this section a brief review of the work ongoing at UWA will be presented.

3.1 Autonomous sample acquisition

Currently research is being undertaken to increase the amount of science data that can be retrieved within a mission by reducing the amount of time required to take samples and reducing the amount of time wasted while waiting for return communication with Earth. In order to do this it is proposed that a fully autonomous system is required.

The completed system will need to accomplish these tasks;

1. Take image of surrounding terrain.
2. Identify features of interest within terrain.
3. Classify the science value of those features.
4. Create an activity plan.
5. Navigate to within 2 meters of target.

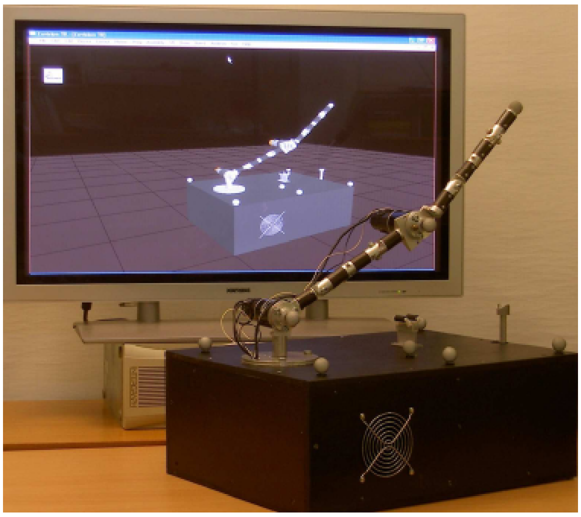

Figure 6: The UWA 3 DoF lightweight manipulator, with arm simulation shown on screen behind.

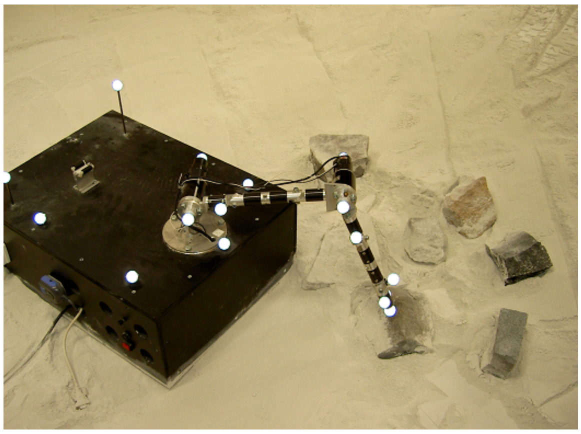

Figure 7: The UWA 3 DoF lightweight manipulator, With End point positioned on target rock

6. Create Three dimensional model of target.
7. Distinguish Best approach to target; Approach which will best facilitate a successful sample acquisition.
8. Move to desired location and re-evaluate target; Create another DEM now that a better viewing location has been reached.
9. Determine best manipulator approach trajectory; Checking that the approach will be of no risk to the manipulator.
10. Take Sample.

During this process, if anything goes wrong or a sample is considered unreachable, the system will abort the sampling process and continue its search for suitable science targets.

There are several challenges to be overcome before such a system could be realized;

- Encapsulation of a human expert's knowledge.
- Identification of plausible science targets.
- Prioritization of recognized targets.
- Onboard DEM generation.
- Robotic arm Inverse kinematics and collision checking.

Encapsulation of a human expert's knowledge. A planetary geologist Derek Pullan (Pullan, 2006) has created an internal report for an ongoing scientific autonomy project, it details what information a planetary geologist would be interested in if they were able to visit Mars. The information is presented in the form of several tables detailing the feature of interest along with a science value score. This aspect of the system is as yet un-implemented but it is proposed that this data will be utilized in order to produce a rule set enabling an expert system to identify science targets based on the criteria set out by the human expert. Table 1 shows an example of the information provided.

ID	**Feature**	**SVS**
T000	Signature: No Texture	0
T001	Signature: Textural	5
T002	Quality: Distinct signature	50
T003	Quality: Indistinct signature	5
T004	Fabric: Random	5
T005	Fabric: Orientated	50
T006	Fabric: Imbricated	100
T007	Surface: Dull	5
T008	Surface: Polished	50
T009	Surface: Rough	10
T010	Surface: Striated	50
T011	Surface: Concoidal	100
T012	Surface: Vesiculated	10
T013	Surface: Pitted	40
T014	Surface: Bumpy	50

Table 1: Table showing the an arbitrary science value score (SVS) according to textural features (Pullan, 2006).

Identification of plausible science targets. In order to identify plausible science targets from the images captured by the rover's panoramic cameras, the features within the image must first be identified. Several methods have been utilized in the past to accomplish this including; height maps (Fox et al., 2002), identification of shadows and a more direct feature extraction approach where by the features are identified directly from the image. The later approach has been adopted here. Image processing techniques such as Watershed segmentation, edge detection and region growing are all utilized in order to identify regions of interest within a image. These regions of interest can then be further examined for rock-like properties.

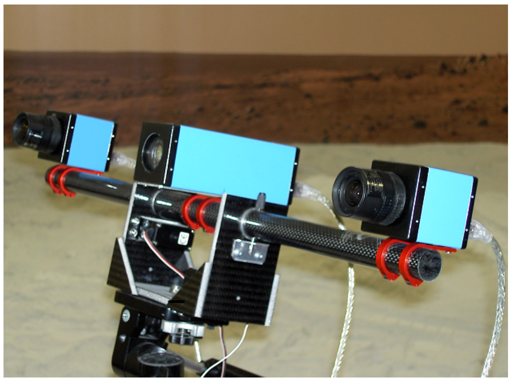

Figure 8: The UWA Panoramic (PanCam) Camera equipment

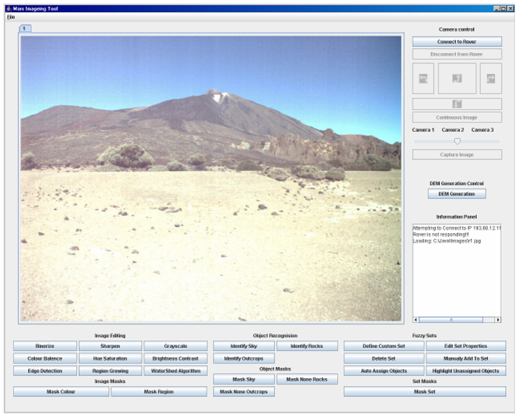

Figure 9: UWA Autonomous sample selection software, Showing image taken using UWA PanCam by Dave Barnes on field trip to Tenerife

Although in the future a great deal of benefit could be derived from running this software autonomously onboard a planetary rover, the present computational demand of software of this nature dictates that it is run on Earth. This being said an Earth based system can demonstrate the possible advantages of such a system while improving confidence that such a system is viable and potentially very rewarding. It is to this end a "Mars imaging tool" has been produced. This software (shown in Figure 9) controls the rovers on-board cameras (Onboard camera setup is shown in Figure 8) once an image is retrieved from the cameras the software is able to process it looking for rocks and other geological features of interest.

Several different feature extraction methods are uti-

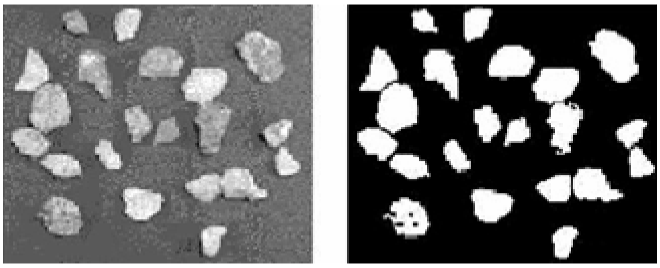

Figure 10: Example of image segmented using watershed algorithm (Farfan et al.,)

lized during this stage. One that has been found to be very promising is the Watershed algorithm (Farfan et al.,). This algorithm is a region growing style algorithm which is capable of producing some very impressive results (Figure 10 shows the types of results possible through use of this algorithm).

Prioritization of recognized targets. Once potential targets are identified they will need to be processed and attributed a science score. This part of the system is as yet un-implemented, but it is proposed that a fuzzy logic approach be used to determine the science value of targets based on the information provided by a human expert (Pullan, 2006). A fuzzy approach will allow us to deal with uncertainty as well at the hard facts.

Onboard DEM generation. DEM generation is now a well established field and can be accomplished very accurately with a high level of resolution (Scharstein and Szeliski, 2002). The problem however is that computational power is very limited onboard a planetary rover. This means that any DEM generation algorithm used would have to be both efficient and resource friendly. As time progresses this problem will be reduced as space qualified computer hardware will be faster and more powerful. It is because of this that it has been decided no new DEM generation technique would be examined in relation to this project. It is thought that by the time an onboard DEM generation ability is necessary the computational power will be available.

Robotic arm Inverse kinematics and collision checking. Robotic arms have become a constant feature of past and future planetary exploration. With this in mind a large amount of research has been done into the autonomous deployment of such an arm. The SCAIP (Huntsberger et al., 2005) project is one such project, and has laid the way for further research to be undertaken. Currently the integration of a similar system into our autonomous sample identification system is being proposed. Having these two systems integrated will provide a number of benefits, by enabling sample acquisition to begin while initial images are being downloaded to Earth.

Protection of the robotic arm is also of high priority, if taking a sample will put the robotic arm or any other

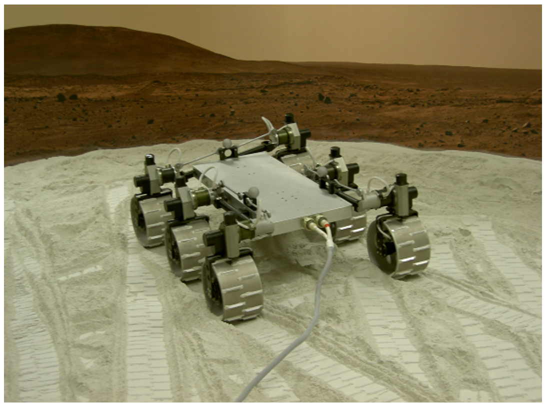

Figure 11: Photo. of the UWA Concept-E rover chassis.

part of the rover at risk the sample acquisition would be aborted. The robotic arm has the ability to damage itself if wrongly guided, checks will have to be made in order to ensure that this will not happen. Initially a simple bounding sphere collision checking method will be implemented.

Current work has progressed to using the UWA's three degree of freedom lightweight manipulator (Figure 6) to simulate a rover's manipulator. This enables us to work initially on the problem of merging coordinate systems so that the rover can autonomously position its end effector on the target location (Figure 7 Shows an example of how this would be done).

It is thought that such a system could drastically reduce the amount of time currently needed to take a sample on Mars (Huntsberger et al., 2005).

4. Additional Future Work

Currently work is progressing on the system in the early development stages. The rover chassis is operational (all be it by tethered control), the Pancam is built and a robotic arm is available for development purposes. Once each individual module is completed it will be possible to integrate these parts to produce a complete test bed. As it is still quite early in the project it is difficult to know what the main stumbling blocks will be, but currently it is thought that they will include;

- Rock mass and outcrop identification.
- Production of a reliable fuzzy feature classifier.
- Production of a schedule planner.
- Minimal memory and computational cycle time DEM generation (or suitable alternative).
- Light weight manipulator collision avoidance and protection.

During the next year the project team here at UWA plan to have overcome these problems. The next stage will then be to integrate the system and test it with available equipment. This integrated test bed will then provide the facility for further research into the autonomous planetary scientist to be undertaken.

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