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(2020)

A probabilistic based UAV mission planning and navigation for planetary exploration.

In *Proceedings of 2020 International Conference on Unmanned Aircraft Systems: ICUAS'20*.

Institute of Electrical and Electronics Engineers Inc., pp. 594-599.

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<https://doi.org/10.1109/ICUAS48674.2020.9213933>

# A Probabilistic based UAV Mission Planning and Navigation for Planetary Exploration

Julian Galvez Serna, Felipe Gonzalez, Fernando Vanegas and David Flannery

**Abstract**—The use of Unmanned Aerial Vehicles (UAVs) for Search And Rescue (SAR), powerlines, air quality and other applications is increasing. Their use has also been considered for planetary exploration (e.g. Mars, Titan). One exciting development in UAVs is a test planned by NASA of an unmanned helicopter in the atmosphere of Mars; this aims to establish a new dimension and direction for the planetary exploration field. Future missions will require advanced navigation tools supporting mission planning. The autonomy of UAVs systems will continue to grow for Earth applications supported by mathematical tools, models and formulations that help the UAV to deal with critical aspects of the mission. Planetary exploration is challenging and is influenced by different levels of uncertainty in UAV localization and the environment itself. Probabilistic navigation allows planning with uncertainty. This paper presents a high-level mission planning and navigation architecture for planetary exploration based on Partially Observable Markov Decision Process (POMDP). We focus on planetary exploration missions for biosignature detection. The paper presents a mission planning architecture and describes the results of a POMDP-based navigation and target finding module emulating biosignatures with ArUco markers in a Mars simulated environment.

## I. INTRODUCTION

UAVs for Earth exploration and monitoring is an active field of research; some examples include the monitoring of wildlife, reefs, air quality and weeds [1], [2], [3], [4]. Missions to inspect and collect data using UAVs on other planets and moons (e.g. Mars and Titan) have also been proposed [5], [6]. The helicopter experiment that will fly on the Mars 2020 rover is intended to verify some of the challenges and limitations of UAVs as platforms for planetary exploration [5]. UAV platforms can provide additional capabilities in terms of resolution and range. Once UAVs demonstrate a capacity to fly, navigate and follow essential commands in other planetary environments, development is likely to focus on autonomous mission planning and new capabilities enabled by increases in the computational power and sensors available. Literature on UAV mission planning on Earth is rapidly growing [7], [8], [9], [10]. UAV missions in remote and isolated areas on Earth, such as deserts in the USA, Africa, Western Australia, and Antarctica [11] allows testing of autonomous capabilities before missions are sent to deep-space locations [12], [13]. In general, the main objectives of a planetary exploration mission with UAVs on Mars are different to those that take place on Earth. On Earth, missions often focus on resource exploration and monitoring applications [1], [4], [2]. One of the objectives for Mars is to use UAVs to assist scientists in the detection of astrobiologically-significant features, such as biosignatures

and habitable palaeoenvironments, as well as resources that may be available for future crewed missions [14].

Detecting biosignatures on Mars using UAVs requires a sensor and a model to classify the surface from aerial images. Chan *et al.*, [15] prosed probability maps created by observing exposed biosignatures as heat map builds with morphology data, polygonal contours and mineralogy. The morphology is taken from satellite images, using instruments such as the High-Resolution Imaging Science Experiment (HiRISE) on the Mars Reconnaissance Orbiter (MRO). Polygonal contours are derived from image processing and mineralogy from the MRO Compact Reconnaissance Imaging Spectrometer for Mars (CRISM). Once probable places to find exposed biosignatures are found, one possible next step is to conduct a close inspection with a rover or a UAV in order to capture detailed images.

Planetary exploration is regulated by different levels of uncertainty in UAV localization and the environment itself. Probabilistic navigation allows planning with uncertainty. This paper introduces a probabilistic UAV mission planning and execution architecture for biosignature detection that applies to both missions on Earth and Mars. The design of a UAV for planetary exploration needs to include several constraints and careful mission planning, which may also benefit applications on Earth.

This paper is organized as follows: Section II presents the mission formulation, goals, steps and assumptions taken. Section III exposes the software and hardware architecture proposed. Section IV formally describes the POMDP formulation to deal with the proposed mission. Section V presents the simulation environment under development. Section VI describes a POMDP formulation for a navigation and target finding problem in the framework implemented, followed by Section VII that shows the results of the navigation module in a Mars simulated environment. Finally, Section VIII presents conclusions and future work.

## II. MISSION FORMULATION

Figure 1 illustrates a possible UAV mission including 1) Landed, 2) Take-off and hovering, 3) Exploring, which consists of collecting data in the horizontal plane, 4) Inspecting, which consists of flight and collecting data in the vertical plane 5) Landing procedure and 6) The possible undesirable crashed status. On Earth, the decision of what state is the next is determined by the pilot's skills or the software used to plan the mission. In most cases, the pilot or software makes a decision based on battery levels and environmental conditions. In the exploration of remote places, there is no

option to let the pilot decide what action is better to pursue. Rapid decisions are fundamental and must take into account the current and projected UAV state based on the sensors; to avoid an undesirable crashed status.

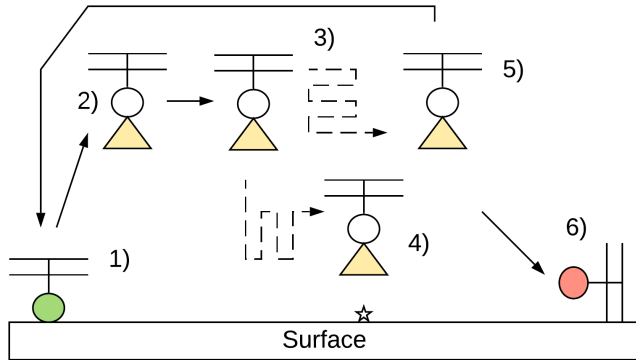


Fig. 1. UAV mission statuses are: 1) Landed, 2) Hovering, 3) Exploration in the horizontal plane, 4) Inspection in the vertical plane, 5) Landing, 6) Crashed. This diagram represents the UAV as a circle (body of the UAV) connected to a double T (the coaxial rotor).  $\Delta$  = downward-facing camera. Green inside the UAV's body indicates a safe status and red an undesirable status.

This paper focuses on an autonomous mission planning formulation to maximise the exploration and inspection tasks. The software for target detection will be treated as a module to be developed in future work. The number of flights and flight time are essential aspects of mission planning. It is also crucial to consider the risk associated with take-off and landing, the battery available, the wind conditions, temperature and the power consumption of the different modules. In order to obtain valuable information, it is desirable to collect the right amount of data, analyse it and return it to the scientific team, without a human in the loop. Valuable data collection is a trade-off between the limitations of the UAV in terms of time spent collecting data, the number of detailed inspections and selecting places with a high chance of featuring a target of interest.

This work is not focused on the challenges in aerodynamic effects on the platform. The mission planning assumes parameters such as pressure, gravity and hardware related to the flight dynamics. Nevertheless, a Partially Observable Markov Decision Process (POMDP) is used as it allows us to model and incorporate different variables on the problem formulation. These include power consumption of the UAV and environmental conditions such as temperature, wind and sunlight available for charging.

### III. SOFTWARE ARCHITECTURE

Figure 2 presents the software and hardware architecture. There are eight modules grouped into three main blocks; the Integrity, Consistency and Mission planning blocks. The Integrity block contains modules that represent the health of the system and the UAV hardware constraints presented in Figure 3. The Consistency block includes the navigation status and an estimation of the proximity of the UAV to safe landing places. Finally, the Mission Planning block

covers the modules for POMDP mission planning, mission execution, data processing (e.g. biosignature detection), and reporting. The eight modules are:

#### A. Mission Planning Module

This module is the main focus of this paper; its primary goal is to define the policy or set of actions to be executed in order to maximise the mission goals. In this paper, we use a POMDP approach as will be described in section IV.

#### B. Mission Context and Report Module (MCR)

In a real mission, it is very important to send and receive information to the scientific team via ground station. The primary function of the MCR module is to collect the outputs from modules A, C and D, format the data and send it to a ground station. In an implemented scenario, this module can change the definition of the other modules, adjusting parameters and initial conditions. However, in this paper, this module is represented only by initial conditions of states.

#### C. Mission Execution Module (MiEx)

Once a set of actions are defined, the actions need a module to activate them. The MiEx module takes areas and coordinates to explore, inspect or land as input from the biosignature detection module; these instructions are used to order the navigation module where to go. Furthermore, it keeps track of the cost of each action, estimating time, battery and risk for each action, and reports it to the MCR module. The mission planning module sees the MiEx module output as a metric that measures navigation uncertainty for the Consistency block.

#### D. Biosignature Detection Module (BiDe)

The primary purpose of this module is to detect a possible target (e.g. biosignature) and provide information regarding possible places to explore or inspect. In this paper, we illustrate the concept by taking the images from a payload sensor (RGB camera) and the  $(x, y, z)$  coordinates of the UAV as input. BiDe gives two-dimensional heatmaps arrays as outputs. The array considers values for a) Dangerous areas to avoid (for landing and flying over), b) Places already explored, c) New places to explore and d) Unknown/undefined places. The BiDe also outputs, a list of inspections instructions, including coordinates and angles at which the images need to be taken.

#### E. Health Monitor Module (HeMo)

This module mainly focuses on the monitoring of hardware health, checking battery voltage, and the response by the sensors after an action is taken. For illustration purposes, this module uses a single discrete variable  $H = [0-10]$ . This value can be determined based on sensor measurements (e.g. battery voltage) and models [16].

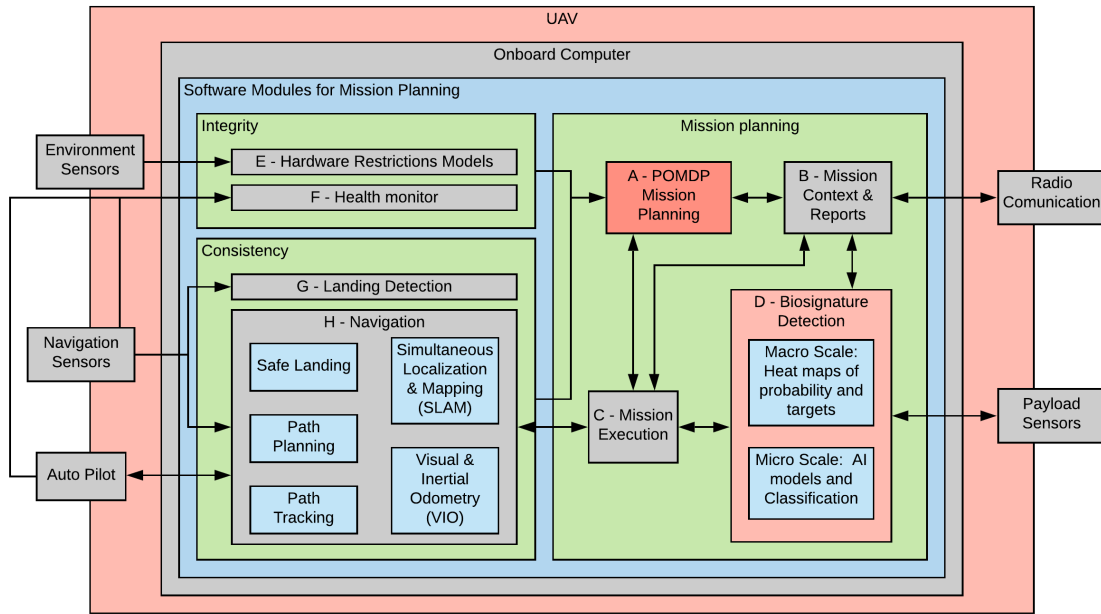


Fig. 2. Proposed software and hardware architecture

### F. Hardware Restrictions Module (HaRMo)

The restrictions for the hardware include the UAV parameters and environmental variables. The most influential environment variables for the UAV include temperature, solar radiation and wind conditions as presented in Figure 3.

Figure 3 illustrates the mission planning constraints and the dependence connection with the environment and the hardware of the UAV.

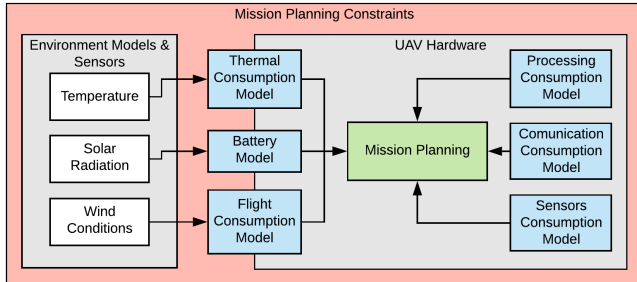


Fig. 3. Hardware restrictions identified, to be included in the mission planning module

Extreme environment temperatures require the UAV to spend its energy to keep the system inside operational conditions. The input energy or solar radiation constrains the amount of energy the UAV can collect. However, solar is used in this paper, given that it will be the method used by the Mars Helicopter [5]. Wind strength and direction have a direct effect of the actions that the UAV has to execute in order to keep the navigation module working. These variables have an impact on battery energy. A way to deal with these variables consists of generating a model that estimates a curve over time interpolated with sensor measurements that forecast future temperature, irradiance and wind values. With

these forecast curves, the module can estimate the amount of time and energy required to conduct charge, keep the system warm and operational for the current or next flight. A value between 0 and 10 is used in this paper as an example. If the hardware is restricted to flight we use 0, and we use 10 if there are no restrictions.

### G. Landing Detection module (LaDe)

One of the most critical parts of the mission is the landing. Detailed conditions must be satisfied by the landing surface to reduce the risk of a crash. This module, which is part of the consistency block, uses a downward-facing camera to detect the percentage of suitable landing surface below the UAV. Several possible landing approaches have been proposed [17]. One possible approach is to use segmentation methods [18], allowing the UAV to estimate how safe it is to fly or land over a particular area. For illustrative purposes in this paper, a percentage of surface suitable for landing is mapped to a value between 0 and 10 to be used and averaged with the other modules in the Consistency block.

### H. Navigation Module (NavMo)

The Navigation module contains all the tools and functions to navigate, locate and execute the actions generated by the mission planning module as instructed by the mission execution module. This module takes as input the target coordinates and the UAV initial location in  $(x, y, z)$  and generates actions to the flight controller to control the movement of the UAV. In this paper the module generates an output value between 0 and 10 associated with the uncertainty in the navigation, in which 0 is high uncertainty in the position and actions and 10 means the navigation is working optimally, locating and taking the actions as expected.

#### IV. POMDP PROBLEM FORMULATION

In this paper, we use a probabilistic based POMDP mission and navigation planner [19]. The main goal of the POMDP formulation is to reduce the risk of the mission, whilst increasing the area being explored and inspected and the value of the data collected. Additionally, the UAV must be aware and monitor the environmental and hardware constraints, keeping safe operational ranges and allowing enough power to keep all systems working. Formally a POMDP is defined by a tuple  $(S, A, O, T, Z, R, \gamma)$ .  $S$  represents the set of states in the environment;  $A$  is the set of actions,  $O$  is the set of observations;  $T$  is the transition function,  $Z$  is the distribution function describing the probability of observing  $o$  from state  $s$  after taking action  $a$ ;  $R$  stands for the set of rewards for every state, and  $\gamma$  is a discount factor.

##### A. State Variables ( $S$ )

We consider each state of the UAV as the tuple  $(St, I, C)$ , the  $St$  variable refer to the status of the mission (Figure 1), we use a discrete number between 1 and 6 as follows: ( $St = 1$ ) Landed status, ( $St = 2$ ) Hovering, ( $St = 3$ ) Exploring or move horizontal, ( $St = 4$ ) Inspecting or move vertical, ( $St = 5$ ) Landing and ( $St = 6$ ) the undesirable status crashed. Moreover, Integrity ( $I$ ) and Consistency ( $C$ ) variables express the average of the outputs of the modules within the Integrity and Consistency block, respectively. On landed status ( $St = 1$ ), the risk associated is low. However, spending a long time on this status without executing a mission is not desirable from the point of view that the UAV is not exploring or inspecting. Nevertheless, it may be have to remain in this status while changing batteries, process the data collected or during part of the data uploading to the ground control station.

##### B. Actions ( $A$ )

The following actions are proposed; however, the framework allows new variables to be included. The actions of the problem proposed include:

- 1) *Stay On the Ground ( $A_1$ )*: This can be executed just from the landed status, there is no risk associated with this action. This action emulates the charging, processing and an idle task.
- 2) *Take-off ( $A_2$ )*: This action involves moving the UAV to a safe altitude before the exploration or inspection.
- 3) *Hover ( $A_3$ )*: This action works as a transition between statuses, including exploring, inspecting, Hovering and before the UAV landing.
- 4) *Horizontal search / Exploration ( $A_4$ )*: This action changes the status to exploring ( $St = 3$ ), in which the UAV is moving between waypoints above the surface, collecting images.
- 5) *Vertical descend / Inspection ( $A_5$ )*: This action sets the status to inspecting ( $St = 4$ ), in which the UAV descends to the surface to collect data with high resolution.
- 6) *Land ( $A_6$ )*: This action finishes a flight, changing from one of the previous flight statuses ( $St = 2, 3, 4$ ) to the landed status ( $St = 1$ ).

##### C. Observations ( $O$ )

The observations for the POMDP formulation is composed of: (1) the status probability; (2) the integrity value obtained from the Integrity block; and (3) the consistency value calculated by the Consistency block.

##### D. Transition Function ( $Tr$ )

The transition function ( $Tr$ ) between the states and the actions are showed in Figure 4. The actions and the transitions they trigger contain a probability for each related state and action. The landed and crashed status are presented in green and red, respectively. The probability of transfer to other states, especially to states with crashed status is conditioned by the  $I$  and  $C$  values of States. A formula  $P(S6|A, S)$  will depend on the  $I$  and  $C$  value as  $1 - (I/10 * C/10)$ , this indicates that as soon as the Integrity (Health and Hardware Restrictions) or Consistency (Landing options and navigation certainty) go down, the probability of end in crashed status is higher.

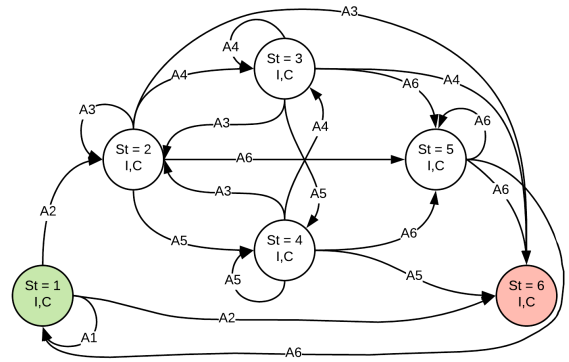


Fig. 4. Transition function representation, in which the circles represent the states, composed by the  $St$ ,  $I$  and  $C$  variables. The representation is grouped by the discrete variable status  $St$ . The arrows indicate a possible transition after taking an action  $A$ . for simplicity and readability, not all possible actions or transitions are present. The green and red color are related to the status landed  $St=1$  and crashed  $St=6$  respectively.

##### E. Reward Function ( $R$ )

Table I lists two possible options for the reward function. Option 1 uses smaller positive and negative rewards where the trade-off between a crashed and inspecting is small. Option 2 uses a two-order of magnitude penalty for crashed. The reward function is strongly related to the states status in this formulation. It is also important to note the intention to maximise the mission time spent inspecting or exploring, and address the negative reward of executing a mission in terms of take-off, hovering and landing, thus avoiding short and risky missions.

##### F. Uncertainty

The primary source of uncertainty comes from the environment, through the hardware restriction module, in the form of the sun, temperature and wind. The other source is within the navigation module for the UAV localization given the dynamic response of the controllers. The uncertainty is updated in the "observation" and the "transition" functions.

TABLE I  
REWARD FUNCTIONS PROPOSED

State status	Reward Option 1	Reward Option 2
Landed	1	-1
Hovering	-1	-5
Exploring	5	5
Inspecting	10	10
Landing	-5	-10
Crashed	-10	-1000

## V. SIMULATION ENVIRONMENT

The framework uses tools such as ROS, Gazebo, Octomap, Rviz and PX4, a Software In The Loop (SITL) for UAV control. This framework is based on the framework for UAV navigation and exploration in GPS-denied environments proposed by Vanegas et al [20].

A simulation of the Mars environment surface is considered for the initial framework. This simulated environment contains a Digital Elevation Model (DEM) of MARS around the landing place of the Curiosity rover in Gale Crater as presented in Figure 5.

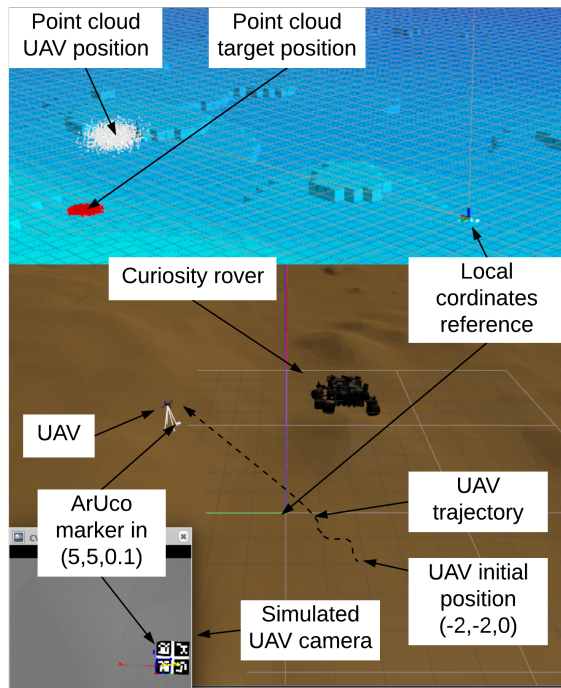


Fig. 5. Current simulation environment, in RViz and Gazebo, in red a point cloud of an inspection target is present, in white, a point cloud of the position of the UAV obtained from the navigation module. A Mars Curiosity rover is used as a surface reference and future ground control.

The Digital Elevation Models were obtained from The Mars Trek Website [21]. This website offers different types of data for Mars, including surface images and elevation models. The elevation models can be downloaded as STL files for 3D printing purposes. It is also possible to generate a Mars surface compatible with Gazebo simulation. The

transformation of the STL files into an Octomap and Gazebo simulator files was achieved using Binvox [22], Viewvox, Binvox2bt and Blender.

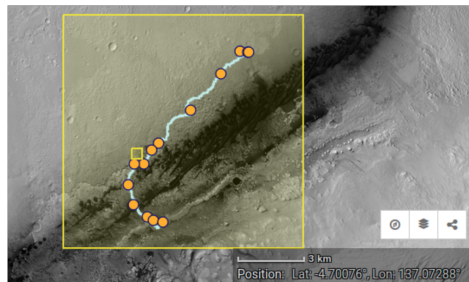


Fig. 6. Images of the Curiosity rover path over Mars over about 2000 SOLs or Martian days (around 37 minutes longer than Earth day). Mars Trek website from NASA [21].

## VI. POMDP MODEL FOR NAVIGATION

The current POMDP implementation starts with a POMDP formulation for the UAV navigation module. A Mars DEM is included. Gravity and flight dynamics are out of this paper scope, given the intention to develop a framework independent of the environment and the platform.

The Framework includes the following POMDP formulation for navigation and target finding, based on Vanegas et al [19], [20] :

1) *State variables (S)*: The states for the lower-level aspects of the UAV navigation module, used when the UAV is in status 2, 3 and 4 are composed of the UAV position and heading angle  $(x_u, y_u, z_u, \Psi_u)$ , the forward and lateral velocity  $(\dot{x}_u, \dot{y}_u)$  and the target's position  $(x_t, y_t, z_t)$ .

2) *Actions (A)*: There are six actions: hover, move forward, turn left, turn right, move up and move down. These actions describe set-points (forward velocity, lateral velocity and altitude) for the UAV motion controller.

3) *Observations (O)*: The observation contains two sources of position estimation one from internal sensors including IMU, compass and barometric pressure. The other source consists of a landmark detection system for the target location if the downward-looking camera detects it.

4) *Transition function (T)*: This function relates the UAV dynamic and kinematic response to motion commands adding uncertainty using a normal distribution representing the deviation and drift in the position between the actions executed.

5) *Reward function (R)*: The reward function is chosen to motivate the exploration of new spaces (+15), avoid collision with obstacles (-70), avoid flight outside the operating airspace (-70) and penalise the energy cost per time step (-10). The reward for finding the target is 500, and the discount factor  $\gamma$  has a value of 0.97. These values were selected based on experimental results on a large number of simulations ( $\approx 500$ )

6) *Uncertainty*: The uncertainty in the motion of the UAV comes from the dynamics of the system, and the controller response to the setpoint requested. This uncertainty is modeled as a Gaussian deviation.

## VII. SIMULATION RESULTS UAV NAVIGATION

Two tests were conducted for two different targets; each test contains twenty runs of the POMDP model in the simulation environment with the DEM of Mars, as presented in Figure 5. A simple ArUco marker is used for illustrative purposes in replacement of the biosignature target. On this simulation, the Navigation module controls the UAV from its initial position to find the biosignature target over the surface. The averaged results are presented in table II. It is notable the decrease in the success rate to detect the target when it is located behind the UAV; this target location requires a longer rotation which increases the drift.

TABLE II

RESULTS OF NAVIGATION TESTS IN MARS SIMULATED ENVIRONMENT

Value	Test 1	Test 2
Target Location $(x_t, y_t, z_t)$	(5, 5, 0)	(-5, -5, 0)
Flight time to target (s)	28.1	28.3
Total reward	348.05	355.08
Success rate (Target detection)	95%	70%

## VIII. CONCLUSIONS AND FUTURE WORK

This paper presents a high-level probabilistic mission planning model, and a low-level UAV navigation module using a POMDP formulation. A number of assumptions in the environment, hardware models and the mission planning modules were necessary to focus and consolidate a high-level mission planning. Initial results show that the POMDP module for navigation can accomplish a short survey mission, detecting the target effectively, but adjustments are required to cover target findings in all surroundings of the UAV. Ongoing work focuses on introducing more complete models of the mission constraints to make more robust estimation and execution of the Consistency and Integrity blocks and the modules on them. Crucial elements to deal with during the mission are the computation load of gathered data analysis, and environmental restrictions which constrain the UAV mission and navigation. The POMDP problem formulation proposed needs a full integration. The current framework covers navigation and exploration. Once the implementation reaches a functional level, parameters such as the reward, transition and observation function, and the models used to estimate the integrity and consistency of each state of the UAV can be enhanced based on statistical comparisons.

## ACKNOWLEDGMENT

The first author would like to thank the QUTPRA scholarship from QUT for funding this project.

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