Validating Mission Relevance of Autonomy Technologies through Increased Science Return

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Abstract

The focus of this paper is to present a methodology for validating the relevance of autonomy technologies to current and future space missions. In this paper, we will discuss the objectives of NASA space exploration missions and explain the requirements needed for autonomy technology to achieve mission goals. By focusing on the underlying purpose of the mission, that of maximizing scientific yield, we will analyze how autonomy technologies address achievement of mission objectives. We will discuss how technologies such as reasoning, planning, and autonomous control, have a direct influence on mission success. The methodology proposed breaks down mission components into operational functions, and discusses how technologies, based on performance metrics, enable achievement of these functions and increases in science return. A specific example of validating autonomy technologies applied to surface exploration missions will be provided.

1. Introduction

The process of infusing autonomy technologies into future space exploration missions is a daunting task. In most cases, missions justify the inclusion of new technology by determining the effect a given technology has on the utility of the mission, which is computed by combining the utility of outcome with the probability of achieving the outcome [1]. The outcome of a mission depends on the mission objectives and can range from traversal of a rover over a given terrain to imaging a distant star. Risk models are used to estimate the probability of success by evaluating whether the technology can meet mission goals in sufficient time. Typically, these probability factors are computed from extensive experimental, and field data, in which performance failure rates are collected from implementing the algorithm on analogous hardware systems. Maximizing the utility function then enables the creation of a ranking criterion for selection of technologies. For autonomy technologies, especially at low maturity levels, this evaluation process is not always sufficient to understand the benefits of infusing autonomy into the mission scenario. Typically, extensive terrestrial experiment data, or field data, implemented on analogous hardware systems is not always available. Probability factors for assessing failure rates may be qualitative, versus quantitative. And other factors, which relate autonomy technologies directly to increased mission return, such as science density and mission survivability, are not usually classified as tangible mission objectives.

The primary purpose of a surface exploration mission is to enable science return [2]. In fact, the Space Science Enterprise, which is responsible for all of NASA's programs relating to the solar system, strategizes investment in research efforts that can "maximize the scientific yield from our current missions" [3]. An autonomy technology can therefore be linked to achievement of mission goals by evaluating the impact it has on science return. The concept of science return though is a difficult value to measure. Naively, we can say that a technology that increases the quantity of measurements provided by a mission also increases science return. Continuing in this vein, we can say that a technology that increases the success probability of increasing the quantity of measurements increases science return. Theoretically, this process flow can continue on indefinitely. To this effect, a framework must be constructed that systematically relates technologies to science return in a structured fashion. This will enable development of a methodology that allows autonomy technologies to quantify the scientific benefit they bring to the mission, thus providing a means to validate to mission designers the need to embed autonomy technology directly into mission scenarios.

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2. Mission Operational Functions

The first stage required to validate the relevance of autonomy technologies to current and future space missions is to decompose mission scenarios into operational functions. The integration of technology into NASA exploration missions can occur at three distinct operational levels: on-Earth, in-Space, and/or at-Surface. These operational opportunities are interlinked to enable the mission to target the best sites for detailed measurements and increased science return. As an example, Figure 1 summarizes the operational steps for the Mars surface exploration mission strategy [4].

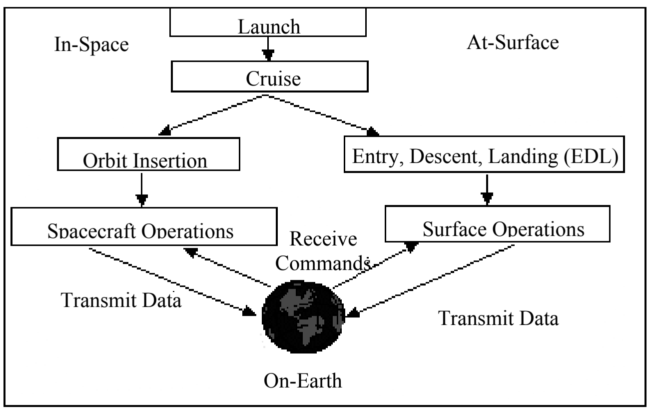

Figure 1: Operational stages for exploring Mars

The mission operational functions can further be subdivided into functional sequences and functional sequences into functional steps. For example, in the upcoming Mars Exploration Mission (MER), surface operations can be separated into the three functional sequences: Mobility, Approach/Instrument Placement, and Sample Handling [5]. Subsequently, functional steps for Mobility include actions such as *Acquire panorama image, locate scientific site of interest, Plan path toward goal,* etc.

Through operational functions, missions are designed to achieve a given set of science goals, where science return is evaluated based on the number of high priority measurements achieved by the mission [6]. To enable science return, technologies must directly address at least one of three components: *quality of scientific measurements, quantity of scientific measurements, and/or range of scientific measurements*. Based on this concept, the value of a technology is assessed by determining how a technology impacts each of the three science return components.

3. Technology Hierarchy

To successfully achieve mission objectives, integration of technology can occur at different levels in the mission scenario. A technology that performs on-board resource planning to extend mission life effects science return, just as does a technology that reduces the data dimensionality of science measurements transmitted to Earth. As such, a hierarchy that categorizes the technology in relation to the science return components must first be constructed, such as shown in Figure 2.

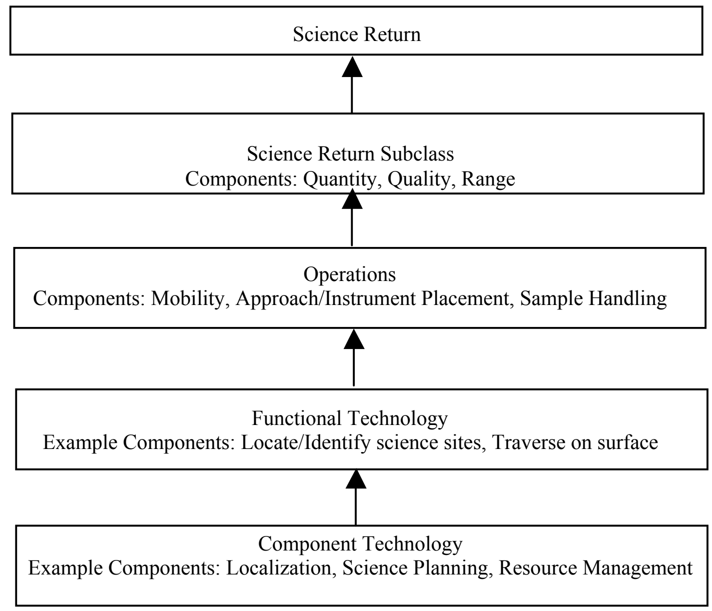

Figure 2. Hierarchy linking autonomy technologies to science return

At the highest level is science return, with the three science return components located at the science return subclass level. Below the subclass level is operations, which represents the functional sequences associated with an operational function of the mission. At the next level are technologies that execute steps associated with a functional sequence. The last level in the hierarchy is the component level. Resident at this level are technologies that enable achievement of the functional steps. Example technologies include: localization techniques, opportunistic science planning, and on-board resource management.

4. Technology Impact on Science Return

Performance metrics are defined to capture important attributes of each technology, as relates to its associated technology level. The performance metrics are characteristic of how the technology impacts the technology level. For example, a *mobility* technology, which is resident at the functional level, has performance metrics that relate to distance traveled per sol, whereas a *localization* technology, which is located at the component level, has performance metrics that relates accuracy to distance traveled.

The performance parameters of a technology may differ from other technologies in the same level. For example, a performance metric for a *science planning* technology (resident at the component level) is related to science sites. On the other hand, the performance metric for a *localization* technology (also resident at the component level) is related to accuracy. To enable reasonable comparison of different technologies, a unified template that characterizes technologies in terms of four factors is utilized. The four factors segment the performance parameters into classes that represent the task dependencies (inputs), the task results (outputs), the environmental constraints (environment), and the resource constraints. In addition, in order to enable multiattribute validation and ultimately understand the impact of technologies on the mission, performance parameters must be normalized into a unitless measure. Technology impact is therefore calculated based on normalizing the difference between technology performance and the performance of current baseline State-of-the-Art (SOA) technology, such that:

$$\text{Technology Impact Score} = \frac{1}{w} \sum \frac{\square_c - \square_c}{\square_c}$$

where w is the number of performance metrics available for assessing the component, $\square_c$ is the SOA capability with respect to the performance metric, and $\square_c$ is the capability of the technology with respect to the performance metric. This difference value is summed over all performance metrics common to the technology. Once calculated, the Technology Impact Score (*TIS*) for that level is then determined such that:

$$\text{Technology Level Impact Score } (n) = \frac{1}{w_n} \sum TIS$$

where n represents the technology level in the hierarchy, w_n is the number of components resident at that level, and the value is summed over all components resident at the n^{th} level. To propagate the Technology Impact Score up the hierarchy, Technology Impact Scores for each component are determined and used to determine the Technology Level Impact Score for the next level.

$$\text{Technology Impact Score } (C_i, N) = \frac{1}{w_i} \sum TIS\,(\text{i, N-1})$$

$$\text{Technology Level Impact Score } (N) = \frac{1}{w_N} \sum TIS\,(C_i, N)$$

where N is the next level in the hierarchy, C_i are the components resident at level N, w_i is the impact weight of component i divided by the number of related components from the previous level. The Technology Impact Score is summed over all components at the $(N\text{-}1)^{th}$ level that are linked to component i at level N. The Technology Level Impact Score is then computed by summing over all Technology Impact Scores for components resident at the N^{th} level. Since the highest level of the hierarchy includes the science return components, the Technology Impact Scores calculated at the final level represents the technology impact on science return.

5. Validating Autonomy Technologies for Surface Exploration Missions

As an example, we selected two autonomy technologies, reconfigurable robots [7] and terrain-based navigation [8], to determine their impact on future Mars surface exploration missions. We began by constructing an in-depth analysis of the functional sequences and steps required for Mars surface exploration missions. In this analysis, there are three main sequences required for surface exploration: Mobility, Approach/Instrument Placement, and Sample Handling. The Mobility sequence has three steps: 1) locate scientific site of interest, 2) plan path toward goal and 3) execute drive to goal. The Approach/IP sequence has four steps: 1) locate scientific target, 2) perform short-range traverse to target, 3) deploy instrument, and 4) place instrument on target. The Sample Handling sequence has five steps: 1) locate scientific sample, 2) plan path to retrieve sample, 3) execute path to retrieve sample, 4) transport sample to processing unit, and 5) analyze sample.

Once the hierarchy was created, we collected performance metrics for the two tasks and propagated the Technology Impact Score calculated at the functional level to determine impact on science return. The objective of the reconfigurable robotic technology is to combine autonomous learning and software reconfiguration with modular hardware components to construct small, fault-tolerant robotic vehicles. As relates to the three science return components, the performance characteristics of this task increases the quantity of scientific measurements and range of scientific measurements. Terrain-based navigation involves incorporating perception-based terrain assessment and soft computing techniques for navigation on rough terrain. This task improves the quality, quantity, and range of science by allowing access to “interesting” science sites. The following table shows the assessment process for the two tasks.

Reconfigurable Robotic Technology

PERFORMANCE PARAMETERS	units	SOA Value	Technology value	Normalization
System Capability				
Inputs				
No dependencies				
Outputs				
Effective Speed	cm/sec	0.20	5.00	0.96
Distance traversed	km	0.1	5	0.98
Environment				
No improvements	unitless			
Resources				
Mobility Modes	unitless	1	5	0.80
Technology Impact Score				0.69
Technology Impact Score (Mobility)				0.69
Technology Level Impact Score (Operations)				0.23
Technology Level Impact Score (Science Return Subclass)				0.15
Technology Impact on Science Return				0.15

Terrain-Based Navigation

PERFORMANCE PARAMETERS	units	SOA Value	Technology value	Normalization
System Capability				
Inputs				
No dependencies				
Outputs				
Effective Speed	cm/sec	0.20	0.40	0.50
Distance traversed	km	0.10	0.50	0.80
Environment				
Surface Complexity	traversability	0.2	0.9	0.78
Surface friction	unitless	0.8	0.5	0.60
Resources				
No dependencies/management				
Technology Impact Score				0.67
Technology Impact Score (Mobility)				0.22
Technology Level Impact Score (Operations)				0.07
Technology Level Impact Score (Science Return Subclass)				0.07
Technology Impact on Science Return				0.07

The Technology Impact Score for the reconfigurable robotic task is calculated by summing up the improvements of the technology over the SOA. The task affects all three functional steps of the Mobility sequence, thus the Technology Impact Score for the Mobility Component is calculated as 0.69. Since, the reconfigurable robotic technology does not affect the Sample Handling or Approach/Instrument Placement sequences, the Technology Level Impact Score for the Operations Level is calculated as 0.69/3. The reconfigurable technology affects two of the three science return components, namely quantity of scientific measurements and range of scientific measurements. Thus, the Technology Impact on Science Return is calculated as 0.15.

The terrain-based navigation task affects only the *navigation* functional step of the Mobility sequence, thus the Technology Impact Score for the Mobility Component is calculated as 0.22. Since, the navigation technology does not affect Sample Handling or Approach/Instrument Placement, the Technology Level Impact Score for the Operations Level is calculated as 0.22/3. The navigation technology affects all three of the science return components, namely quantity of scientific measurements, quality of scientific measurements, and range of scientific measurements. Thus, the Technology Impact on Science Return is calculated as 0.07.

From this analysis, we conclude that reconfigurable robotic technology has a larger impact on science return than terrain-based navigation. Intuitively, this makes sense since the reconfigurable task effects more operations at the lower level and is typically a high-risk, high-return technology as applied in most areas. In this case, future work will need to incorporate success probabilities to ensure that more mature technologies can fairly be compared to high-risk, less mature, technologies.

6. Conclusion

In this paper, we have presented a methodology for validating the relevance of autonomy technologies to current and future space missions. The objective of NASA space exploration missions is quantified in terms of science return, and achievement of those objectives is represented as a set of mission operational functions. Technologies are then linked to the mission through a hierarchy that associates performance metrics directly to science return. The methodology presented allows a means to validate the need for autonomy technology by developing a structured approach for assessment. Future work will involve incorporating probabilities of success in the analysis to enable consistent comparison of technologies at different maturity levels.

7. References

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