The Final Frontier: Autonomous Space Exploration, Trajectory, and Economics

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1 INTRODUCTION

Against the backdrop of incessant societal advancement, few of humanity's collective projects have truly been regarded as speculative while entailing astronomical amounts of resources in nature – the only historical examples being the pursuit of divinity, the thirst for profit, and war [8]. Space exploration currently stands to be written into history as one such momentous project characteristic of our generation.

Space exploration while teeming with grandeur for the meaning it can bring to humanity, be it finding resources for a new way of life or a fundamental quest for knowledge, nevertheless has been fraught with challenges. Conventional human-supervised or manned space missions are simply too risky and costly [1] to be conducted at scale. Put into perspective, every astronaut sent to Mars would require the delivery of 500,000 tons of cargo costing several hundred billion dollars [5], along with the severe risk to human life should a mission go awry.

Autonomous space exploration thus surfaces as a unifying solution that will rebalance the disproportionate costs and risks attributable to space missions [1], seeking to accord machines the role of executing high-stake tasks, and the autonomy to decide task should be conducted [6].

The challenges presented by autonomous space exploration spans notable facets including software, hardware, engineering capabilities, as well as overarching economic conditions to make funding of such projects viable. The scope of this paper will be restricted to aspects pertaining to computer science that enable and enhance computer autonomy in space exploration.

Section 2 will discuss the history of how autonomous space exploration systems was spurred. Section 3 will examine key technological aspects of such systems. Section 4 will delve into economic aspects of autonomous space projects. Section 5 will discuss the trajectory and catalysts. Section 6 will provide ending remarks for this paper.

2 Pursuit of Autonomy

2.1 History and Precursor

The Deep Space One (DS-1) spacecraft was perhaps the most instrumental project that paved the way for development into autonomous space exploration. As part of NASA's New Millennium Program that was launched in 1998, the DS-1 was intended to test new technologies at that point in time [2], of which autonomous operation and navigation stood as one of the most remarkable in the domain of artificial intelligence.

The key advanced technologies comprised propulsion and energy systems, autonomous systems, measurement systems, telecommunications and microelectronics; the arm of autonomous systems comprised autonomous navigation (AutoNav), a remote agent, and a beacon monitor [10]. While the DS-1 flight accomplished numerous feats in space exploration, the success of the AutoNav system remained as a reliable precursor to how spacecrafts could be designed to make decisions with limited to no human intervention, spurring the development of modern autonomous spacecrafts capable of venturing into new frontiers in space.

2.2 Motivation

The project holds instrumental value as autonomous space exploration currently stands as one of the most viable solutions for accomplishing space missions that present steep technical challenges. One of the fundamental goals for NASA in developing autonomous systems that aid space exploration was how human intelligence would no longer be viable in space operations, due to system and mission complexity, rapid reaction time needed, time lags in communication from spacecraft to Earth or other base of operations, and harsh environments [11].

3 Technology of Autonomous Space Exploration

3.1 Aspects of Autonomy in Space

Rational Agent

In a bid to formulate a framework in analyzing technological aspects of autonomous space exploration, we have to consider how these systems, be it unmanned spacecrafts, rovers, or simple vehicles, are in fact rational agents that operate or interact with some larger environment. With respect to rational agents and environments, Russell and Norvig have defined [13]:

- an agent is an entity that perceives a larger environment through sensors
- an agent is able to take action that either affects itself or the environment through actuators
- an agent acts according to some defined agent function that maps a sequence of percept vectors as perceived from its sensors, to some action in a defined in some set of available actions

Task Environment

Furthermore, to contextualize the purpose of such rational agents that are meant for autonomous space exploration, we can non-exhaustively define each component of the agent's task environment [13] as follows:

- **Performance Measure**: speed in executing a space mission, accuracy in navigation, precision in carrying out mission objectives, prioritizing mission-critical tasks dynamically, searching and analyzing objects of interest, resilience and self-recovery
- **Environment**: space, planets, satellites (manmade or natural), asteroids, atmospheres, terrain (water bodies, land, ice, sand, etc.), stars, gravitational fields
- **Actuators**: propulsion systems, land traversal systems, energy recovery systems, communication arrays, mechanical actuators, parachutes and landing systems, flashlight and signaling lights
- **Sensors**: cameras, positioning systems, gyroscopes, engine sensors, microphone, antennas

Autonomous Space Exploration Agents

Autonomous space exploration systems comprise a variety of technologies, such as those delineated below, it is prudent to note that while artificial intelligence accounts for a high degree of autonomy in these systems, it is not the only concept responsible for what makes a system truly autonomous [14]. Indeed, for autonomous systems to work as designed, the task environment described above is pertinent to understand how the states of various technologies are developing, and what uncovered grounds may arise. For instance, in a typical autonomous spacecraft mission, the integrated system would need to derive serializable or quantifiable data from its trajectory in space through its sensors, before a preprogrammed agent function can process such data to arrive at an optimized action to take. These actions could range from elementary adjustments in propulsion vectors to correct its course, or act on some object of interest.

Autonomy in itself, according to Schroer, exists along a continuum which can be conceptualized as a 10-level model where Level 1 denotes full human control with delineated increasing levels of autonomy up to Level 10, in which computers are capable of rationalizing if a given task should be executed if at all [6].

In fact, more specific for vehicles pertaining to space exploration, autonomy can also be regarded as both of [12]:

- ability to satisfy a set of mission objectives in a predetermined timeframe without external intervention, such as from humans
- capability to execute mission tasks or obtain deliverables, such as taking precise measurements or recover objects of interest

To enable the autonomous space systems of tomorrow, autonomous space systems would need to demonstrate the capability of achieving higher levels of autonomy in the model described by Schroer, such that space missions can be executed in more challenging environments where human intervention has limited viability. The technologies delineated below also support the enhancement of either criteria of how these systems can achieve a higher degree of autonomy.

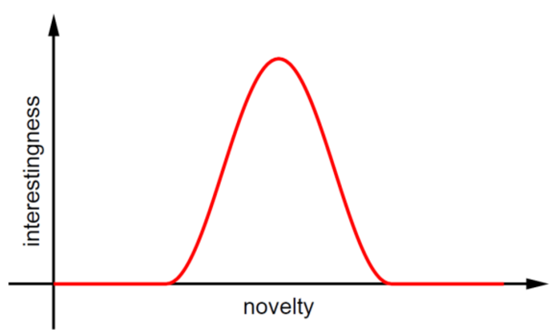
3.2 Artificial Intelligence and Decision Processes

While systems capable of autonomous space exploration comprise several different technologies, it is noteworthy that artificial intelligence is a significant catalyst that propels the advancement our endeavors in this field. At least in the scope of decision processes and onboard operations, artificial intelligence in decision processes accounts for much of the optimizations available.

Curiosity and Novelty

For humans, curiosity for the unknown is a fundamental building block in our quest for knowledge. This attribute that vary across people often shape the way we think, or actions we take to achieve our goals. For non-autonomous space missions in the yesteryears, manifesting such curiosity is arguably easier when astronauts can either be placed onboard to assume direct control, or pass on sequences of instructions through code to unmanned spacecrafts via some ground base of operations.

Extending such curiosity as a driving force for actions taken to autonomous space exploration systems would require novel advancements in artificial intelligence models. Graziano et al. posit a notion of interestingness in which the concept of artificial curiosity machines can emulate would guide its course of actions [1].

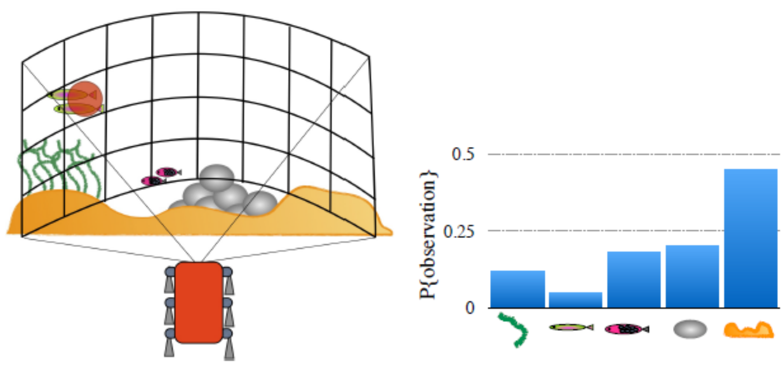


Wundt Curve [1]

They argue that while autonomous space exploration systems should seek to optimize how it achieves mission goals or relay significant information back to Earth, the nature of space exploration in itself teems with the unforeseeable such that building systems based on a priori information would not render the system able to know what is interesting relative to challenges presented in space [1]. The Wundt curve above shows how Graziano et al. argue that there is a critical amount of novelty needed in some observation for it to be deemed interesting, and repeated trivial observations would be less interesting in time.

Simulating Curiosity

Indeed, this closely emulates how human agents perceive observations in our greater environment. To model such curiosity for machines, Girdhar and Dudek employ realtime online topic modeling (ROST) to compute a quantifiable measure of perplexity of features observed in the environment by the autonomous system, which could range from terrain types or lifeforms, to highlight topics of interest [15].



Illustrative Example of Recognizing Novel Objects Using ROST [15]

In their study, which was supplemented with real life images such as corals and various 2D datasets, an autonomous system placed in a hypothetical scenario with an abundance of sand and rocks, along with some corals, would identify the fishes demarcated in the red circle as the most novel observation as represented by its corresponding topic, and attempt to change its exploration path in favor of these fishes [15].

This is due to the various observations the system has already made in its exploratory path, where green fishes are underrepresented in the distribution of observations on the chart. As such, in a bid to simulate curiosity and obtain more information on less encountered objects, the autonomous system would seek to optimize its course of action to the green fishes.

Curiosity Reward

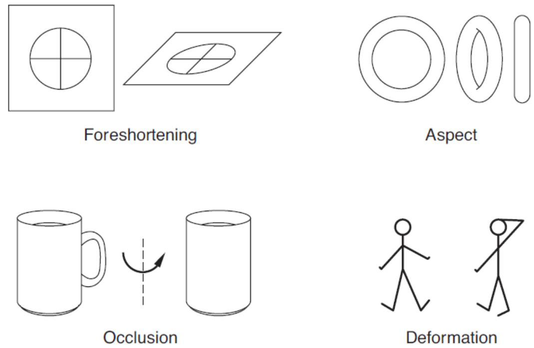
To further augment the course of action to take when encountering objects of interest, we could accord some form of curiosity reward that can be used as a feedback signal such that the autonomous system can optimize the ideal action to take given a set of observations, as evidenced in projects like IM-CLEVER [1]. Thus, such technological advancements enable autonomous space exploration agents to carry a more optimized agent function, and engage in decision processes that take in input from its sensors, and outputting a form of action through actuators.

3.3 Computer Vision and Navigation

For autonomous space exploration systems, besides making optimized actions to meet mission requirements, recognizing and categorizing inputs from camera images are significant aspects of the technology needed for autonomy to be successful. However, the way humans and machines perceive visual data is vastly different. Autonomous systems capture images in the form of pixels, and the challenges associated with identifying how a region of pixels map to some known feature is a meaningful one that will be discussed below.

Appearance and Pattern Elements

Elementary objects per se already present challenges for machine recognition. In space where conditions are more dynamic and harsher, technology in machine vision will have to be sharpened for accuracy in making correct associations.



Variations in Appearances [13]

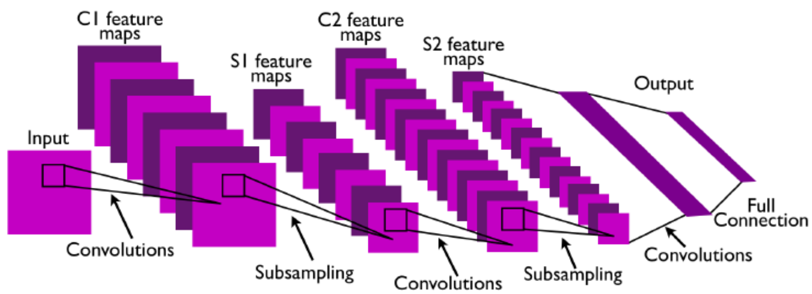
Major sources of appearance variations are highlighted above, and in the context of autonomous space systems [13]:

- **Foreshortening** effects cause objects to be perceived as slanted, for instance from some spacecraft approaching a target object from some altitude
- **Aspect** effects cause objects to look vastly different from different angles, for instance when a rover camera is directed at the same object but from different bearings to the object
- **Occlusion** effects entail some part of an object being covered, for instance when a camera is directed at a meaningful object of interest, but some terrain feature covers part of it
- **Deformation** effects entail change in degrees of freedom for a given object, in the context of autonomous space systems that are not designed to interact with relatively large sentient beings, this effect could arise more often if some external condition on a planet for instance such as wind could cause a target object to move

If such effects are not accounted for, this would lower the accuracy for machines to recognize a given object or feature correctly, and possibly jeopardizing a given space mission.

Convolutional Neural Networks

Fortunately, advances in artificial intelligence have yielded novel approaches in tackling these challenges. Convolutional neural networks, as inspired by the work of Hubel and Wiesel on the visual cortex [16], are able to use multiple convolution pooling layers to discern features that can later be identified from some input image [17].



Convolutional Neural Network Architecture with 2 Feature Mappings [18]

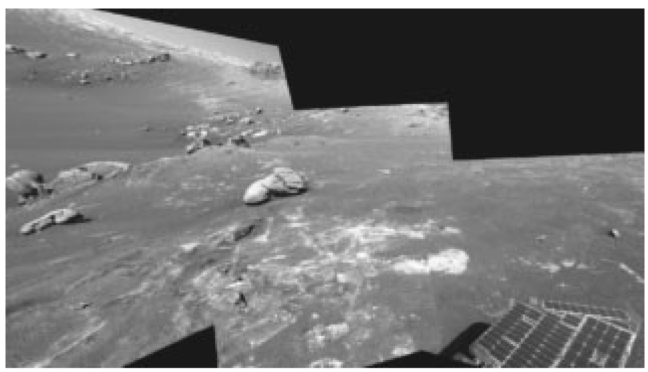
While a particular convolutional neural network (ConvNet) depends on implementation and design, with popular tools such as PyTorch being readily available, the above architecture shows how a typical ConvNet can be designed. In essence, given an input image, repeated convolution and subsampling stages can be applied on each color channel of an image to yield feature maps that represent features obtained from regions in the input image, and eventually arriving at some desired output classification for features in the image [18].

Convolutions that can be applied may vary across implementations, but a respectable architecture in the context of the ImageNet LSVRC-2010 contest, that involved sorting 1.2 million images into various classifications, entailed the use of overlapping pooling for instance; the traditional concept of pooling summarizing a region of $z \times z$ pixels by a meaningful average or maximum over pixel values spaced s pixels apart, was augmented with setting the spacing value s to a value less than z, such that each region pooled effectively overlaps with some previous region pooled [19].

Thus, for optimizations in decision making on the part of autonomous space exploration systems to be achieved, advances in computer vision are crucial for these systems to be able to recognize features in space, and such technology could serve as the backbone for ROST as described above to have accurate features already mapped before further analysis on features to be explored can be made.

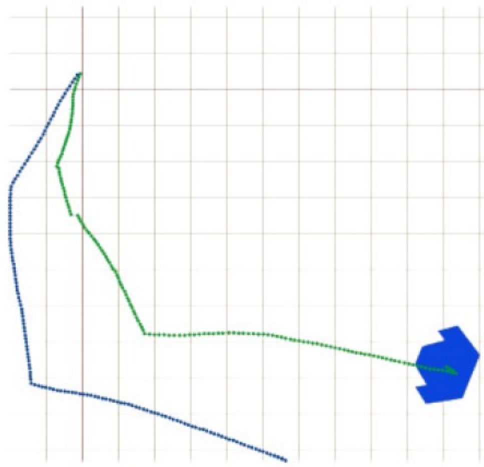
Feature Tracking and Visual Odometry

While the hardware in cameras is an important aspect for quality of computer vision in order to correctly discern between objects and the larger environment an autonomous space system is in, we will focus more on the software capabilities. Computer vision is quintessential in identifying features for instance, and as covered above helps the system track what features it has to navigate through or act on.



Superimposed Images of Opportunity Rover for Visual Odometry [4]

In planetary exploration rovers, the images collected by the rover are mostly taken in multiple shots and superimposed as the system is moving. In the above image, we see how Mars Exploration Rovers are able to track features across pairs of images. This is enabled by the fact that feature detection is made possible first as described above, before performing a correlation-based search to determine a rover's position in space from just 2D images [4].



Augmented Navigation Data with Visual Odometry [4]

A more rudimentary method of navigating across terrain would simply be to use revolutions in the wheels or belt of a rover for instance. However, visual odometry is particularly useful as it yields more accurate data as terrain in space do not observe the same traction as roads in modern day society, wheels could be slipping in sand, or the rover could be traversing a slope in which case data from wheel encoders may not present accurate 2D data, as seen in the image above. The Opportunity rover's visual odometry capabilities tracks terrain and is able to yield the accurate path in green, as compared to what would have resulted from data gathered from wheel encoders in blue [4].

Disparity Matching

Other methods of enabling visual odometry are also possible, a notable one of which is presented by Kostavelis et al. in the form of disparity matching, whose name implies that the system seeks to find disparities in images from a pair of cameras placed close to each other to obtain slightly different views, known as a stereo placement [3].

Disparity Map from Stereo Image Pair [3]

$$\mathrm{AD}(x, y, d) = \left| I_{\mathrm{left}}(x, y) - I_{\mathrm{right}}[(x - d), y] \right|,$$

$$\mathrm{DSI}(x, y, d) = \sum_{i=-w}^{w} \sum_{j=-w}^{w} \mathrm{gauss}(i, j)\, \mathrm{AD}(x + i, y + j, d),$$

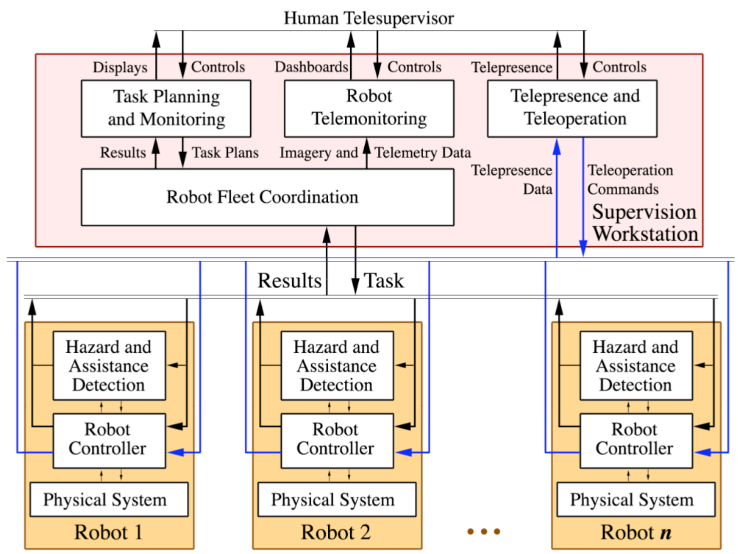
$$\mathrm{disp}(x, y) = \arg\{\min[\mathrm{DSI}(x, y, d)]\}.$$

Equations for Computing Disparity Map [3]

Note that as the stereo cameras are always placed a fixed distance apart on a given autonomous rover, analyzing stereo image pairs can help both with depth perception and also forming accurate disparity maps to improve visual odometry. The above shows how stereo-vision produces the disparity map by first taking the absolute difference AD across intensity values I from the left and right images, d is the disparity value (note that the left camera is the base image; a disparity space image matrix DSI is then initialized to keep track of matching costs and disparity values, by considering fixed sized squares and taking a Gaussian-weighted sum over the absolute differences; and finally finding the disparity value for a given pixel *(x, y)* by finding the minimum value on the d-axis [3]. Such techniques then go on to improve the state of the art by yielding more accurate feature tracking and ultimately navigation capabilities.

3.4 Fleet Networks

While an individual autonomous space system might be able to accomplish specific mission tasks efficiently as designed, there are other various other tasks in the context of space missions like mining, transportation, repairing works, or construction, where having scaling the number of autonomous systems proportionate to the time expected to accomplish the aggregated task might prove more efficient [5].



Robot Supervision Architecture (RSA) with Human Supervision [5]

Podnar et al. presented how RSA helps a human controller supervise a fleet of autonomous robots to accomplish some pooled larger task, by having each robot autonomously do smaller pieces of the task in which a human controller would find difficult to micromanage, but can a human controller can optimize the priority of tasks and monitor how the fleet of robots is performing at any time through a supervision interface, and reallocate resources as needed [5]. While it is prudent to note that the RSA is not completely autonomous in that human intervention is needed for it to work, it nevertheless is a significant advancement in enabling autonomous fleet development.

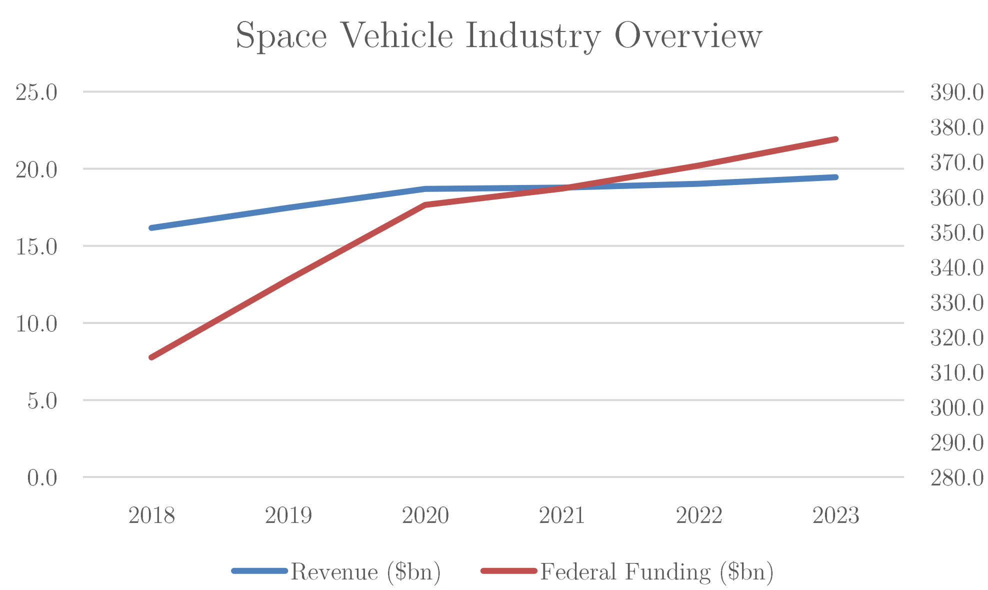
While fully autonomous fleet systems have seen limited usage in space exploration, possibly due to the risks and costs that will be discussed in later sections, the possibility and needs for their adoption is nevertheless clear. Distributed Space Systems (DSS) that are fully autonomous involve a fleet of autonomous space systems achieving a unified mission, either cooperatively or uncooperatively depending on whichever is most efficient at each given timestep as decided by how the entire system autonomously decides, and could exist as micro-spacecrafts to spread out the cost of losing singular spacecrafts since they each unit is cheaper to manufacture [20].

4 Economics

In a bid to understand more about the economics pertaining to autonomous space exploration systems, it is quintessential to analyze the scope of the industry, sources of funding, unit economics of autonomous space systems or projects.

4.1 Industry Overview

Autonomous space exploration systems fall under a larger umbrella industry that includes the manufacturing of space vehicles as well as missiles; while the overall industry revenue is $28.6bn overall, only approximately 56.5% of the industry based on products and services segmentation is accrued to non-missile systems [21].



As we are concerned with only the space industry, in the chart above, I have accounted for the segmentation of both industry revenue and federal funding by using the non-missile segmentation proxy of 56.5% applied onto primary industry data for the umbrella industry as provided [21].

Additionally, from the chart in 2018, industry revenue is about $16.2bn and associated federal funding is about $314.1bn. The space industry is a rather mature one, as the barriers to entry into this industry are high due to the capital required and research spending needed to build reliable space systems, as such this could explain how the whole industry is growing relatively slowly annually at 3.8% for the next 5 years; federal funding presented a downward trend entering 2018, but is expected to grow through 2023 [21].

4.2 Notable Stakeholders

Various stakeholders play an integral role in enabling the development of autonomous space exploration technologies [21]. Such stakeholders contribute to the state of the art through various channels, such as through funding, or development of related research or technologies that directly or indirectly contribute towards autonomous space exploration systems. Also note that these stakeholders span the spectrum of being public government entities, or commercial companies, some of the most notable are outlined below.

Publicly Affiliated

- **U.S. Department of Defense (DoD)**
- **Defense Advanced Research Projects Agency (DARPA)**, an agency of the DoD that invests in breakthrough technologies for national security, of which space exploration forms a pillar of their projects of interest [22]
- **National Aeronautics and Space Administration (NASA)**
- **U.S. Air Force (USAF)**
- **U.S. Space Force (USSF)**, proposed to Congress, a full-time military service aimed to position itself towards national interests in space [24]

Commercially Affiliated

- **SpaceX**, private aerospace manufacturer
- **Boeing**, integrated aircraft and aerospace manufacturer
- **Northrop Grumman**, integrated aerospace manufacturer
- **Lockheed Martin**, integrated aerospace manufacturer

4.3 Space Project Costs

To put the scale of costs related to space missions into perspective, a typical project to send a shuttle into space costs around $450m [24]. Clearly, with such a cost associated with each mission, absent of further costs pertaining to autonomous technologies, space missions can be deemed as prohibitively costly to be done repeatedly, even though private players like SpaceX have in recent years pushed for reusable spacecrafts aimed to reduce the cost of space missions, as mission costs can be expected to decrease if part of spacecraft can be reused for some successive mission [25].

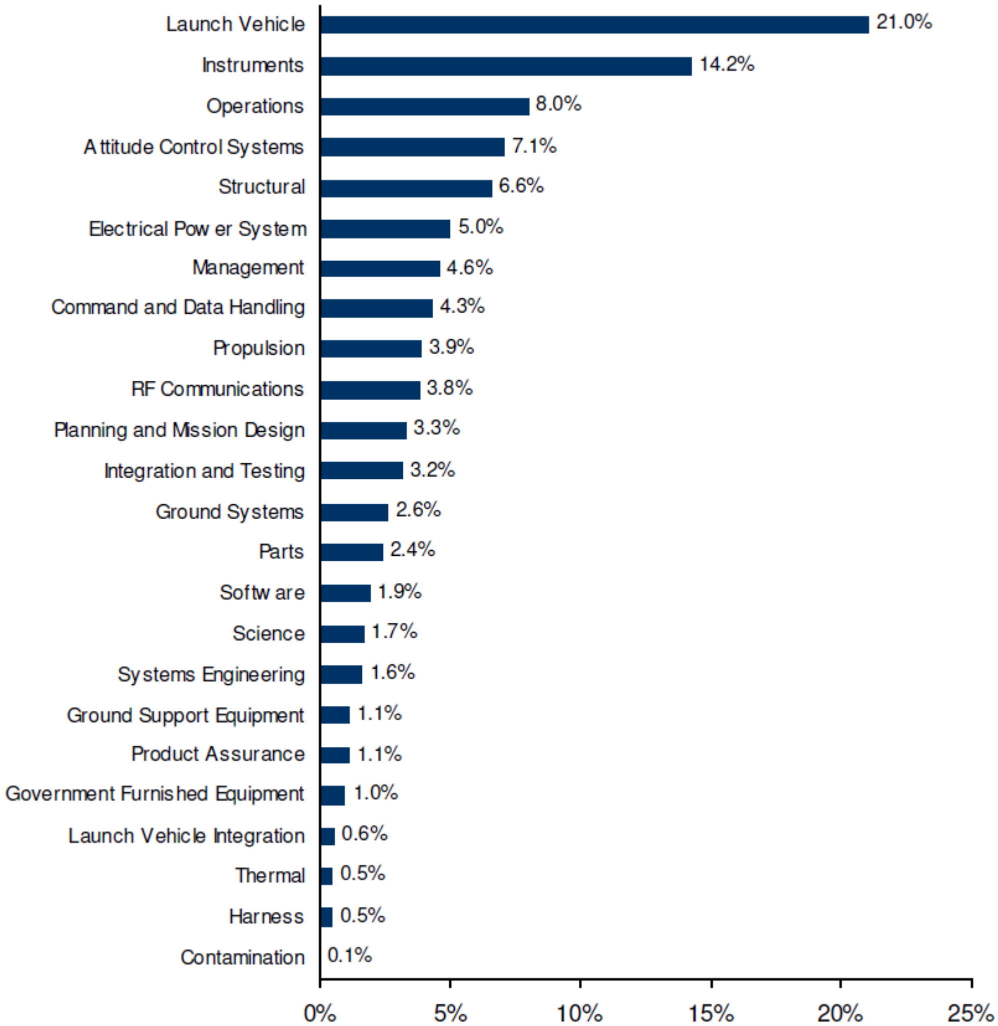
Need for Autonomous Space Exploration

The argument for autonomous space exploration is clear in the modern-day context when the potential for technology has reached higher bounds that was impossible in yesteryears. As we set our sights into newer frontiers in space, sending the first ever astronaut to Mars in the 2030s has been humanity's new ambition [27]. However, even a mission to explore a neighboring planet poses prohibitive costs. Every astronaut sent to Mars would require the delivery of 500,000 tons of cargo costing several hundred billion dollars [5]. Clearly, such space missions simply cannot be replicated at scale as they pose severe cost constraints such that not even the U.S. with one of the highest expenditures in the world for space exploration [21] can sustainably fund such projects.

Moreover, while this cost is largely monetary, the cost associated to the risk of human life simply cannot be quantified. One need not look further than the Space Shuttle Challenger Disaster in 1986, in which Shuttle Challenger broke apart only 73 seconds into its flight and killing all seven of its crew [28], to grasp the gravity of the disproportionate risks associated with sending humans into space.

Thus, more than ever, the need for autonomous space exploration technologies has become increasingly dire, both from a financial and moral standpoint.

Cost Breakdown



Hypothetical Cost Breakdown of a Space Mission [26]

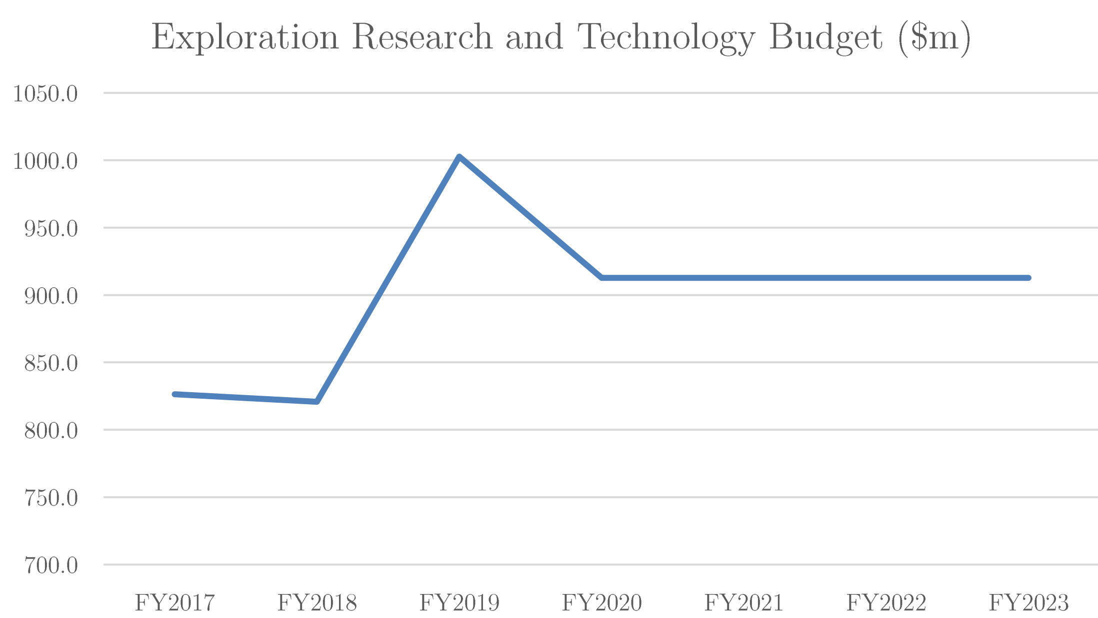
The exact cost breakdown of a space mission varies based on mission complexity and requirements, for instance complex missions requiring the need to perform extremely accurate measurements or conduct intricate operations on a given space environment would arguably be capital intensive for the hardware capabilities required as well as labor hours needed to develop software to drive the overall system. However, a cost breakdown of a typical space mission is provided above. Expectedly, launch vehicle and instruments costs account for the most due to the precision in engineering capabilities required [26].

With the rising need for autonomous technologies in space, costs associated to autonomous software design, associated systems and hardware, integration and testing would likely increase. Thus, in order for autonomous space technologies to be developed, associated spending has to increase.

4.4 Autonomous Space Exploration Spending

NASA Spending Projections

As NASA is one of the leading drivers for autonomous space exploration development, it is worthwhile to study how autonomous technology spending is accounted for in their budget [29].



Autonomous operations are parked under the Exploration Research and Technology budget of NASA, and has been projected to increase in FY2019 to $1002.7m, and tapering off to $912.7m in future years possibly due to uncertainty of whether the state of autonomy can reach designated goals. Furthermore, NASA also reinstated that autonomous capabilities would be pursued in Airspace Operations and Safety Program ($90.8m), which leads research into autonomous aviation systems including Unmanned Aircraft Systems; as well as Space and Flight Support ($903.7m), which also delves in autonomous navigation for near Earth and deep space operations [29]. Such efforts demonstrate NASA's commitment into developing autonomous space technologies.

4.5 Cost Benefit Analysis

While there is no publicly available information on the exact cost wise component for each autonomous space exploration part, we can still perform a cost benefit analysis to see how compelling switching from manned mission to autonomous space missions would be.

Cost Benefit Analysis (NPV)					
Rate (%)	**Benefit ($m)**				
	40	**45**	**50**	**55**	**60**
3%	1.3	24.2	47.1	70	92.5
4%	-3.8	18.4	40.7	63	85.2
5%	-8.7	12.9	34.6	56.2	77.9
6%	-13.4	7.7	28.7	49.8	70.8
7%	-17.9	2.6	23.1	43.6	64.1

I performed a cost benefit analysis as above, using NPV as a metric to measure the outcomes. This analysis is highly conservative even in the base case. I used the cost going into Year 0 of the investment of switching into autonomous space systems as an increased spending of $181.9m based on NASA's financial projections [29], assuming 100% of this difference went into only autonomous development which is unrealistically conservative but nevertheless prudent as I do not want to overstate benefits.

Next, there are various benefits that could be considered. The most direct of forms would be how the autonomous system contributes to mission success, for instance in measurable accuracy of data collected, or some quantifiable benefit such as exploitatively mining resources from planets or asteroids [26, 31]. While I believe these benefits are very clear, they are either hard to quantify due to lack of data, or have too narrow a scope to extend to all autonomous space missions as a whole, respectively. Thus, I ultimately chose the most direct factor to use as a form of benefit, which is the cost savings that can be accrued to having one less astronaut on board a space mission, using the training cost of $50m per astronaut as a proxy [30].

In reality, certainly more than one astronaut can be spared from switching away manned missions to unmanned missions, but again note that this analysis is extremely conservative. We note that from the sensitivity table above, at a modest discount rate of 5% for NASA or space manufacturing companies in general existing in a mature company, we see that the marginal benefit is compelling even under these conservative estimates, as these NPV values are a realistic lower bound as to how much positive incremental NPV developing autonomous space exploration technologies can bring.

5 Trajectory

5.1 Public Developments

Federal Funding

The future trajectory of autonomous space exploration will be highly sensitive to government spending, as the US government is one of the largest players in the market and any funding decisions for space exploration in general will have spillover effects to various government agencies such as DARPA or NASA, which are key drivers in the research and development of such autonomous capabilities in space [21].

Government Agencies

Fortunately, as established above that federal funding will increase over the next few years, we can expect this to serve as a viable catalyst for autonomous goals to be met, propelling the technology to higher levels under Schroer's model [6]. While there is a distinction in the scope of DARPA and NASA in the field of aerospace development, it is worthwhile to note that at least in developing autonomous systems, they have both established plans in place.

DARPA funding is more correlated with defense spending [21], and recently initiated the Fast-Lightweight Autonomy (FLA) program that seeks to enable new technologies for high-speed navigation across dense environments [32]. NASA with its long history of delving in autonomous space exploration systems since the DS-1 [2], have recently considered even integrating blockchain technology into new generation autonomous systems with improved processing capability [33]. All such initiatives could not have been possible without public funding, and would have an instrumental impact in shaping the state of autonomous space exploration in the years to come.

USSF Inception

Lastly, the inception of the USSF could also serve as a catalyst with an initial budget request of $72.4m, before rolling over to $500m annually upon full establishment, as reported in the USSF factsheet, and potentially nudges the state of autonomous technology upwards [23].

5.2 Commercial Development

While more constrained by resources, commercial companies in the space vehicle manufacturing industry are nevertheless key players that can effect change in the state of autonomous space exploration technology. This is because while there is less of a focus on national security or scientific exploration which is in stark contrast relative to players like DARPA and NASA, such companies are involved in sectors such as space tourism, or even have affiliations with NASA for instance, such that developing autonomous capabilities from a part of their keystone strategy to succeed moving ahead [23].

One of the most notable advances is the autonomous precision landing of rockets as exhibited by SpaceX Falcon 9, in which computations to calculate the descent trajectory for the rocket has to be done quickly and accurately all through its autonomous software, such that the landing achieves 99% accuracy, thereby allowing the rocket to be reused for successive missions [34].

6 Conclusion

In conclusion, we see that the need for development in autonomous space exploration is compelling, as it would circumvent limitations of costs and risks associated with having repeated manned missions to space. Especially in the context of today's world where technological advancements happen at scale, the rolling out of a new generation of autonomous space exploration systems is well within reach.

Notably, we see that the infrastructure in terms of technology is well established, and further developments are relatively incremental, in which paradigm changes are less likely. While there could always be even more novel ways of implementing how autonomous systems make optimized decisions in space, or have better software capabilities in computer vision, newer implementations will likely be founded upon the same principles.

In contrast, the state of technology might be more correlated or even possible dependent on the economics as discussed earlier on, as funding on the part of government accounts for much of the resources available in the first place. On the commercial aspect, while the players might have less resources, their profit-maximizing motives still enable to stay as relevant as players in this market as they will seek to develop autonomous technologies that either serve a direct economic purpose for themselves, or could even be sold to other buyers in the market who demand state of the art technology.

Ultimately, with potential catalysts spurring the promising trajectory of autonomous space exploration technology, the future teems with grander frontiers in space that we have yet to explore, and ours is the generation that will see this paradigm change.

7 References

[1] Graziano, V., et al. "Artificial Curiosity for Autonomous Space Exploration." *Acta Futura*, no. 4, 2011, pp. 41–51., doi:10.2420/AF04.2011.41.

[2] Hedberg, S.r. "AI Coming of Age: NASA Uses AI for Autonomous Space Exploration." *IEEE Expert*, vol. 12, no. 3, May 1997, pp. 13–15., doi:10.1109/64.590067.

[3] Kostavelis, Ioannis, et al. "SPARTAN: Developing a Vision System for Future Autonomous Space Exploration Robots." *Journal of Field Robotics*, vol. 31, no. 1, 2013, pp. 107–140., doi:10.1002/rob.21484.

[4] Maimone, Mark, et al. "Two Years of Visual Odometry on the Mars Exploration Rovers." *Journal of Field Robotics*, vol. 24, no. 3, 10 Jan. 2007, pp. 169–186., doi:10.1002/rob.20184.

[5] Podnar, Gregg, et al. "Human Telesupervision of a Fleet of Autonomous Robots for Safe and Efficient Space Exploration." *Proceeding of the 1st ACM SIGCHI/SIGART Conference on Human-Robot Interaction - HRI 06*, Mar. 2006, doi:10.1145/1121241.1121298.

[6] Schroer, Michael R. "Automation in Planetary Rovers." *Air University Press*, 2016, pp. 13–20. *JSTOR*.

[7] Truszkowski, W.f., et al. "Autonomous and Autonomic Systems: a Paradigm for Future Space Exploration Missions." *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)*, vol. 36, no. 3, 2006, pp. 279–291., doi:10.1109/tsmcc.2006.871600.

[8] Tyson, Neil deGrasse. "The Case for Space: Why We Should Keep Reaching for the Stars." *Foreign Affairs*, vol. 91, no. 2, Mar. 2012, pp. 22–33. *JSTOR*, Council on Foreign Relations.

[9] Yamauchi, Brian. "A Frontier-Based Approach for Autonomous Exploration." *Proceedings 1997 IEEE International Symposium on Computational Intelligence in Robotics and Automation CIRA'97. 'Towards New Computational Principles for Robotics and Automation*, July 1997. *IEEE Xplore*, doi:10.1109/CIRA.1997.613851.

[10] "Deep Space 1 Asteroid Flyby." NASA, 1999.

[11] Allen, Danette B. "Trusted Autonomy: Autonomy and Autonomous Systems at NASA LaRC's Autonomy Incubator." NATO IST -136. NASA, 2016.

[12] Kounev, Samuel, et al. *Self-Aware Computing Systems*. Springer International Publishing, 2018.

[13] Russell, Stuart J., and Peter Norvig. *Artificial Intelligence: A Modern Approach*. 3rd ed., Pearson, 2018.

[14] Fong, Terry. "Autonomous Systems: NASA Capability Overview." 24 Aug. 2018.

[15] Girdhar, Yogesh, and Gregory Dudek. "Modeling Curiosity in a Mobile Robot for Long-Term Autonomous Exploration and Monitoring." *Autonomous Robots*, vol. 40, no. 7, 2015, pp. 1267–1278., doi:10.1007/s10514-015-9500-x.

[16] Hubel, D. H., and T. N. Wiesel. "Receptive Fields, Binocular Interaction and Functional Architecture in the Cats Visual Cortex." *The Journal of Physiology*, vol. 160, no. 1, 1962, pp. 106–154., doi:10.1113/jphysiol.1962.sp006837.

[17] Zhang, Tao, et al. "Current Trends in the Development of Intelligent Unmanned Autonomous Systems." *SpringerLink*, Zhejiang University Press, 4 Feb. 2017.

[18] Y. LeCun, K. Kavukcuoglu, and C. Farabet, ''Convolutional Networks and Applications in Vision,'' in Proc. IEEE Int. Symp. Circuits Syst. (ISCAS), May/Jun. 2010, pp. 253–256.

[19] Krizhevsky, Alex, et al. "ImageNet Classification with Deep Convolutional Neural Networks." *Communications of the ACM*, vol. 60, no. 6, 2017, pp. 84–90., doi:10.1145/3065386.

[20] D'Amico, Simone, et al. "Miniaturized Autonomous Distributed Space System for Future Science and Exploration." *International Workshop on Satellite Constellations and Formation Flying*. Delft, The Netherlands: International Astronautical Federation's Astrodynamics Committee, 2015.

[21] Soshkin, Maksim. *IBISWorld Industry Report 33641b: Space Vehicle & Missile Manufacturing in the US*. IBISWorld, 2018.

[22] "Defense Advanced Research Projects Agency." *Defense Advanced Research Projects Agency*, www.darpa.mil/about-us/about-darpa.

[23] "DOD Submits U.S. Space Force Proposal." *U.S. DEPARTMENT OF DEFENSE*, www.defense.gov/explore/story/Article/1767808/dod-submits-us-space-force-proposal/.

[24] Bray, Nancy. "Space Shuttle and International Space Station." *NASA*, NASA, 28 Apr. 2015, www.nasa.gov/centers/kennedy/about/information/shuttle_faq.html.

[25] Shanklin, Emily. "Reusability." *SpaceX*, SpaceX, 23 Mar. 2013, www.spacex.com/reusability-key-making-human-life-multi-planetary.

[26] Gerlach, Charles L. "Profitably exploiting near-Earth object resources." *Proceedings of the 2005 International Space Development Conference, National Space Society, Washington DC*. 2005.

[27] Daines, Gary. "NASA's Journey to Mars." *NASA*, NASA, 13 Feb. 2015, www.nasa.gov/content/nasas-journey-to-mars.

[28] NASA. “Remembering Space Shuttle Challenger.” *NASA*, NASA, 9 Mar. 2015, www.nasa.gov/multimedia/imagegallery/image_gallery_2437.html.

[29] “FY 2019 Budget Request: Exploration Research and Technology.” 2018, www.nasa.gov/sites/default/files/atoms/files/fy_2019_mission_fact_sheets.pdf.

[30] Zubrin, Robert, and Robert Zubrin. “How Much Is an Astronaut's Life Worth?” *Reason.com*, Reason, 26 Jan. 2012, reason.com/2012/01/26/how-much-is-an-astronauts-life-worth.

[31] Diot, Pauline, and Edwige Prohom. "Is there a business opportunity for the exploration of resources on celestial bodies?." *Toulouse Business School* (2018).

[32] Root, Philip. *Fast Lightweight Autonomy (FLA)*, Defense Advanced Research Projects Agency, www.darpa.mil/program/fast-lightweight-autonomy.

[33] Howell, Elizabeth. “Debris-Dodging Spacecraft Could Use Bitcoin-Like Technology.” *Space.com*, Space Created with Sketch. Space, 18 Apr. 2018, www.space.com/40338-autonomous-spacecraft-avoid-debris-blockchain.html.

[34] Blackmore, Lars. "Autonomous precision landing of space rockets." *Frontiers of Engineering: Reports on Leading-Edge Engineering from the 2016 Symposium.* National Academies Press, 2017.