System design concept of Mars Intelligent Imaging & Atmospheric Research CubeSat Constellation using Distributed Deep Learning (MIIAR)

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Planetary observation nanosatellites are increasingly popular since they can be deployed quickly and inexpensively. In this paper, we have designed an innovative and intelligent planetary mission for imaging targeted locations and atmospheric study on Mars from a constellation of nanosatellites. The MIIAR constellation consists of two sets of total seven CubeSats, each for a specific task and function and each set deployed in a specific orbit. The first set is a data relay CubeSat, named as Mothership Data Relay Satellite (MS-DRS), containing three 12U units deployed in the aero-stationary orbit of Mars, whose principal mission is to relay data to Earth from the observational CubeSat deployed on Mars. In addition, the Daughter Ship Type-I CubeSat (DS-I) and Daughter Ship Type-II (DS-II) is a cluster of four 6U observational satellites, deployed in the high inclined orbit of Mars, containing dedicated instruments, for research and study of Mars' atmosphere and hyperspectral imaging of its surfaces. Another important module, a low powered Deep Learning accelerator is included for the first time in a real-time system (to our best knowledge) to perform various machine learning and deep learning operations on board when required and shared among the constellation, creating a Distributed Deep Learning platform among the constellation. For advanced communication, we have included a Software Defined Radio (SDR) and an optical wireless communication module that will provide an advanced inter-satellite link and a deep space communication system for the constellation, thus, reducing the sat-failure probability. Through MIIAR, the scientific community can gather detailed information for future human colonization missions on Mars.

Key words: Hyperspectral Imaging, IR emission spectroscope, Distributed Deep Learning, Machine Learning, Software Defined Radio

1. Introduction

Interplanetary observation nanosatellites [1] are becoming increasingly common since they can be deployed quickly and inexpensively. MIIAR is an innovative CubeSat constellation mission designed to characterize the present Martian atmosphere and climate from the surface into the thermosphere using passive radiometric observations at microwave, IR (Infrared) and UV (Ultraviolet) wavelengths. It consists of seven 6U & 12U sized CubeSats with two sets of CubeSats for planetary observation and data relay. The combined set of wavelengths observed by the COTS (Commercial of the Shelf) hyperspectral camera and the IR spectroscopy on the CubeSats, will provide a wide dynamic range that can penetrate through atmospheric particulates in the Martian atmosphere to sense water vapour, CO_2 concentrations, pressure and temperature and winds. Atmospheric water vapour and ice, CO_2 and dust and their respective cycling through the Martian climate system together with the energy and momentum data observed over a Martian year. Using the on-board low-powered Deep Learning accelerator, Distributed Deep Learning based on data parallelism will be applied for parallel real-time classification and analysis of the data, as well as other various machine learning operations, thus increasing the speed and efficiency of the computation ability of the system.

The MIIAR observational satellites will observe Mars from high inclination orbits providing daily pole-to-pole coverage and will process rapidly to sample the entire planet to separate diurnal and seasonal variability and behaviour. The MIIAR data relay satellites would be deployed to the aero stationary orbit of Mars for continuous real time data communication between the observational CubeSats and the Earth.

This paper focuses on the system design in details and the mission operations of the MIIAR constellation, emphases on the science goals and requirements of the mission and concludes with the Distributed Deep Learning model concept for on board image classification and analysis.

2. Background

2.1. Past Mars missions

NASA's Mars Odyssey [2] orbiter entered Mars orbit in 2001. Odyssey's Gamma Ray spectrometer detected significant amounts of hydrogen in the upper metre or so of regolith on Mars. This hydrogen is thought to be contained in large deposits of water ice. The Mars Express mission of the European Space gency (ESA) reached Mars in 2003. It carried the Beagle 2 lander, which was not heard from after being released and was declared lost in February 2004. Beagle 2 was located in January 2015 by HiRise camera on NASA's Mars Reconnaissance Orbiter (MRO) having landed safely but failed to fully deploy its solar panels and antenna. In early 2004, the Mars Express Planetary Fourier Spectrometer team announced the orbiter had detected methane in the Martian atmosphere, a potential biosignature. ESA announced in June 2006 the discovery of aurorae on Mars by the Mars Express.

In January 2004, the NASA twin Mars Exploration Rovers named Spirit (MER-A)
and Opportunity (MER-B) [3] landed on the surface of Mars. Both have met and exceeded all their science objectives. Among the most significant scientific returns has been conclusive evidence that liquid water existed at some time in the past at both landing sites. Martian dust devils and windstorms have occasionally cleaned both rovers' solar panels, and thus increased their lifespan. Spirit rover (MER-A) was active until 2010, when it stopped sending data because it got stuck in a sand dune and was unable to reorient itself to recharge its batteries.

On 10 March 2006, NASA's Mars Reconnaissance Orbiter (MRO) [4] probe arrived in orbit to conduct a two-year science survey. The orbiter began mapping the Martian terrain and weather to find suitable landing sites for upcoming lander missions. The MRO captured the first image of a series of active avalanches near the planet's North Pole in 2008.

The Mars Science Laboratory [5] mission was launched on November 26, 2011 and it delivered the Curiosity rover on the surface of Mars on August 6, 2012. It is larger and more advanced than the Mars Exploration Rovers, with a velocity of up to 90 meters per hour (295 feet per hour). Experiments include a laser chemical sampler that can deduce the composition of rocks at a distance of 7 meters.

MAVEN orbiter [6] was launched on 18 November 2013, and on 22 September 2014 it was injected into an areocentric elliptic orbit 6,200 km (3,900 mi) by 150 km (93 mi) above the planet's surface to study its atmosphere. Mission goals include determining how the planet's atmosphere and water, presumed to have once been substantial, were lost over time.

The Indian Space Research Organization (ISRO) launched their Mars Orbiter Mission (MOM) [7] on November 5, 2013 and it was inserted into Mars orbit on 24 September 2014. India's ISRO is the fourth space agency to reach Mars, after the Soviet space program, NASA and ESA. India became the first country to successfully place a spacecraft into Mars orbit on its maiden attempt.

The ExoMars Trace Gas Orbiter [8] arrived at Mars in 2016 and deployed the Schiaparelli EDM lander, a test lander. Schiaparelli crashed on surface, but it transmitted key data during its parachute descent, so the test was declared a partial success.

2.2. Hyperspectral Imaging of Mars surface through Reflectance spectroscopy

As defined in [9], exploration of planetary bodies is essential to understand their formation and understanding evolutionary processes leading to their current geological state. The composition of minerals and their atomic structures reflect the physical and chemical conditions under which the planet have formed. Thus, mineralogical studies will provide various data i.e. temperature, pressure, cooling rates of different rock types and therefore help in reconstructing the geological environment that would have been succeeded at the time of their formation. Reflectance spectroscopy is a powerful tool for remote detection of minerals on the earth and other planetary surfaces. It involves measurement of solar reflection from a target in the UV-VIS-NIR (Ultraviolet-Visual-Near Infrared) region of the electromagnetic spectrum in discrete spectral bands. The reflectance value plotted against wavelength produces a spectral reflectance curve, which exhibits characteristic features that are used to identify the specific minerals present, which enables identification of the rock types in an area.

2.3. Present atmospheric study priorities of Mars

According to [10], by NASA, observations of Mars within the past several years have identified methane in the Martian atmosphere, which will likely serve as the catalyst for a brand-new emphasis on trace gas chemistry in the coming decade. The presence of methane, and potentially other trace gases (e.g. SO2) that are not readily formed by Martian photochemistry may reflect surface and subsurface processes previously unknown. Measurements by program developed to measure trace gases reveal that methane varies on Mars with location and season, and provide a more convincing demonstration of the presence of methane than previous observations. This variation is surprising since current photochemical models, which are successful in reproducing observations of atmospheric hydrogen- and oxygen-containing compounds, predict a 350-year lifetime for methane. However, the observed spatial and temporal variability suggests a much shorter decomposition lifetime. Other observations (ground-based and orbital) have yielded basic distributions of ozone and hydrogen peroxide, allowing preliminary validation of first-order photochemical models.

There has been an improved understanding of the dynamics and structure of the Martian atmosphere in recent years, particularly from the missions of TES and MCS, but this knowledge is limited to regions from 10-80 km, which can be observed from orbit. Numerical models, in conjunction with these observations, provides a reasonable approximation of the atmospheric state at locations and times not observed, but also highlight deficiencies in understanding the behavior of the Martian atmosphere.

While these new observations have the potential to answer important questions about this region of the atmosphere, there is still significant work still to do going forward.

2.4. Present CubeSat Planetary observational missions

There are significant operational challenges in interplanetary observational missions [1], due to the dynamic constraints on available energy and access times, unstable orbital properties, and the difficulty in the communicating command and mission data at great distances from the Earth. Spacecraft operations are progressively complex due to the stochastic environments of interplanetary space. For example, gravity and atmospheres at interplanetary bodies may be poorly understood, affecting the orbits and in turn the opportunities for the satellite to collect energy and data and communicate. Operations must be mainly autonomous given the latency delays for interplanetary applications and schedules must be robust to the uncertainties in these environments. Small satellites, such as CubeSats, are an emerging science and technology platform. CubeSats have a standardized 1U (10 cm3 cube) form factor and a standardized deployer that allows them to "piggyback" on rocket launches as secondary payloads; thus they enable low-cost access to space. Emerging sensor and spacecraft technology is enabling small satellites to perform novel science and technology missions, and has been flight demonstrated on several occasions in Low Earth Orbit (LEO). Small satellites are extremely constrained in their ability to collect and store energy and data, control their position and attitude, communicate, and recover from failures due to their small size and mass.

Scientists and engineers are becoming increasingly interested in the potential of small satellite missions to perform novel science and technology demonstration missions at interplanetary targets. The coupled challenges of operating a small satellite in an interplanetary location lead to great operational questions. Thus, there is the need for modeling, analysis, and optimization tools to design feasible and robust operational schedules are required.

2.5. Inter-Satellite Optical Wireless Communication (IsOWC)

As clarified in [11], optical communication is playing an important role in backbone networks for long haul communication. As the multimedia applications are increasing day by day that require high speed data transfer from sender to receiver. This ever-increasing traffic demand is being accommodated using several advancements in optical network technologies. The DWDM (Dense Wavelength Division Multiplexing) system, the improved RoF (Radio over Fiver) optical communication networks and the evolving field of EONs (Elastic Optical Network) are being used to accommodate huge heterogeneous traffic in existing networks. The IsOWC is used for point to point communication at a high data rate. With the increasing demand of real time digital multimedia services, the demand for efficient and economical communication networks that provides high speed wired and wireless access in indoor and outdoor environments. The IsOWC supports high data rate capability, unregulated bandwidth, low power, high efficiency, lesser antenna sizes and low cost but it also have several disadvantages includes the tracking problem and misalignment of transmitter and receiver apertures and the changes due to atmospheric conditions. The tracking problem causes various noise sources such as laser relative noise intensity, Johnson noise, dark current noise. Vibration noise is the most degrading factor in IsOWC communication system. These noises cause errors in the system and made it more susceptible towards the pointing errors. The main aim is to reduce the power dissipation and to reduce the BER. This result in high transmitter power and lesser receiver noise to obtain desired signal.

The system include a laser beam modulated with data and is transmitted through free space with less attenuation in comparison of microwave and RF links as light travels faster in vacuum and can travel a long distance in thousands of kilometres with minimum bit error rate. The system is creditable until the atmospheric disturbances are not present and effect of atmospheric turbulences is heterogeneous for different modulation formats The data rate can be varied from 5Gbps to 20Gbps with a tolerable quality factor. Transmission properties affected due to other parameters include transmission aperture diameter, receiver aperture diameter and power of the operating laser source. The system requires more power when operated at large distances. To avoid the tracking problems the satellites should be in Line-of-Sight links so that transmitter and receiver pointing angles must be precisely confirmed. Signal reception can be intricate or impossible with a small deviation in beam angles.

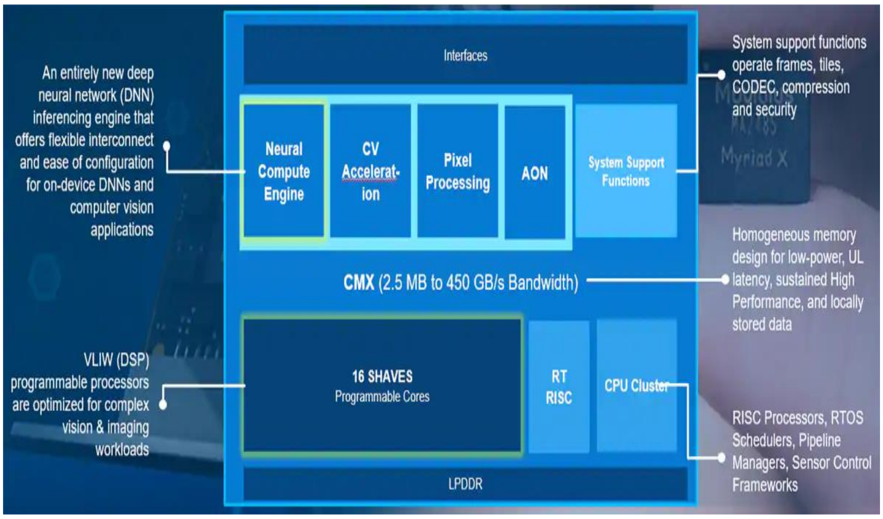

Figure 1. Intel Movidius Myriad X block diagram [22]

2.6. Visual Processing Unit (VPU)/ Low powered AI accelerator

As explained in [12], Vision processing Unit or VPU is a type of microprocessor aimed at accelerating machine learning and artificial intelligence technologies. It is a specialized processor that is made to support tasks like image processing, classification etc. For this, we have chosen the Intel Movidius Myriad X VPU [13], contained in the Intel Movidius Neural Compute Stick 2. Intel's Myriad™ X VPU features the Neural Compute Engine - a dedicated hardware accelerator for deep neural network inferences. The Neural Compute Engine in conjunction with the 16 powerful SHAVE cores and an ultra-high throughput intelligent memory fabric makes Myriad X the industry leader for on-device deep neural networks and computer vision applications. The block diagram for Intel Movidius Myriad X is given on Figure 1. It has an ultra-low power design and contains a programmable architecture, with a small-area footprint. It will be used for advanced computer vision applications for on-board analysis and classification of satellite images using multi layer CNN (Convolutional Neural Network) and AI models, which has been never used to date in an on board satellite system.

2.7. Distributed Machine/Deep Learning

Distributed Machine Learning (DML) [14] is an interdisciplinary domain that involves almost every corner of computer science—theoretical areas (such as statistics, learning theory, and optimization), algorithms, core machine learning (deep learning, graphical models, kernel methods, etc), and even distributed and storage systems. There are countless problems to be explored and studied in each of these sub-domains. On the other hand, DML is also the most widely adopted and deployed ML technology because of its efficiency with Big Data.

Distributed deep learning is a sub-area of general distributed machine learning that has recently become very prominent because of its effectiveness in various applications.

Data parallelism is a parallelization technique that is enabled by partitioning data. In data parallel distributed computing, we first divide the data into a few partitions, with the number of partitions equal to the number of worker machines (i.e. computational nodes). Then, we let each worker own one independent partition and let them perform computation over that data. Since we have multiple nodes scanning the data in parallel, we should be able to scan more data than when using a single node—we increase throughput through distributed parallel computing. In distributed machine learning, where our goal is to speed up the convergence of model training using multiple nodes, applying data parallelism is rather intuitive: we let each worker perform the training (i.e. stochastic gradient descent) on its own data partition and generate a set of parameter updates (i.e. gradients) thereon. We then let all nodes synchronize their parameter states by network communication until they reach a consensus. As long as the synchronization does not take too much time and we see improvement over single-node results, we've achieved our goal! Essentially, this is the way Google's deep learning system DistBelief works.

Compared to data parallelism, model parallelism is a more complex and ambiguous concept. Generally speaking, in model parallelism, instead of partitioning data, we try to partition the machine learning model itself to distribute the workload to multiple computational workers. For example, let's say we are solving a matrix factorization problem where the matrix is super huge and we want to learn every parameter of

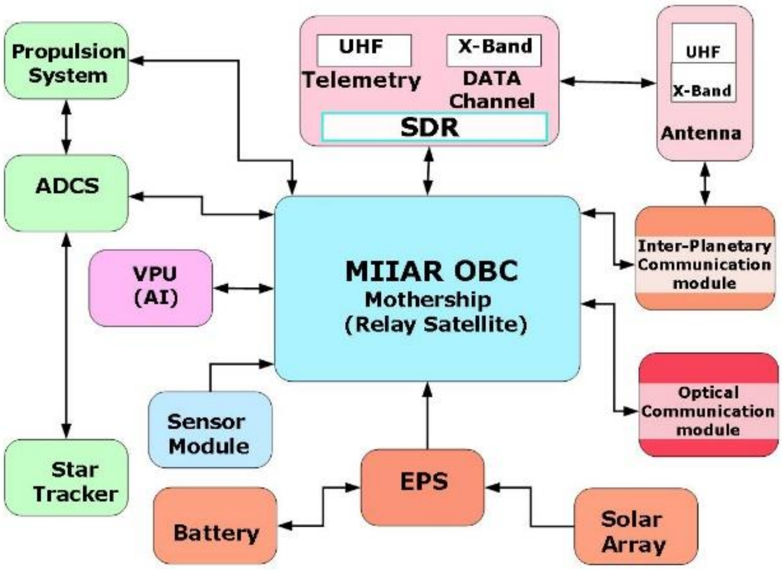

Figure 2. System block diagram of MS-DRS

this huge matrix. To apply model parallelism, we have to partition the matrix into many small blocks (sub-matrices), and then let each worker take care of a few. In this way, we are able to leverage the additional RAM of multiple nodes if the RAM on one node is not sufficient to store all the parameters in the matrix. Since different nodes have different workloads that map to different blocks of the matrix, we should get a speedup when they compute in parallel.

3. System overview

The MIIAR constellation consists of two sets of CubeSats, each for a specific task and function and each deployed in a specific orbit. The first set is a data relay CubeSat, MS-DRS, containing 3 units for complete coverage of the planet, whose principal mission is to relay data to/from Earth from the observational CubeSat deployed on Mars. Secondly, the Daughter Ship Type-I CubeSat (DS-I) and Daughter Ship Type-II (DS-II) is a 2x2 cluster of observational satellite, containing specialized instruments, for research and study of Mars atmosphere and hyperspectral imaging. The system overview diagram is shown in Fig 9.

3.1. Mothership (Data Relay Satellite) (MS-DRS)

The Mothership satellite family is a set of 12U CubeSats for advanced geosynchronous communication that will provide high speed and continuous information and data relay capabilities from Mars to Earth. It will consist of deployable UHF, X band and Ka band antennas with experimental optical wireless communication modules for simultaneous real time data communications. The constellation will be fitted with several Software Defined Radio (SDR) for a complete freedom in frequency choosing for receiving or transmitting data from/to other local planetary missions if required in addition to MIIAR regular operations, which need real time data support from Earth for telemetry and other mission critical tasks. As for the OBC, we have decided to use a modified AiOBC designed and developed as described in [13]. To handle Distributed Deep Learning, the CubeSat will be fitted with an AI-on-the-edge device, a Visual Processing Unit (VPU) that will analyze the numerous observational data and will perform computation based on model parallelism. For trajectory control and station keeping, the CubeSat requires a micro propulsion system to correct the alignment and orbit for stable parking. Each satellite will be powered by deployable solar array containing solar cells, providing power controlled by the EPS subsystem. Lastly, the Earth Communication Module (ECM), will contain a SDR with a RF amplifier for Ka band, for real time communication to Earth through intermediary communication satellites. Keeping in mind the immense constraints of power, mass and volume for a 12U CubeSat, deployable antennas required for high/low gain and optical reflection and the receiver and transceiver module will needed to be chosen wisely so we can get most efficient set of apparatus for reliable data communication. The antenna system accompanied with Irish radio transponder used in the MarCO mission

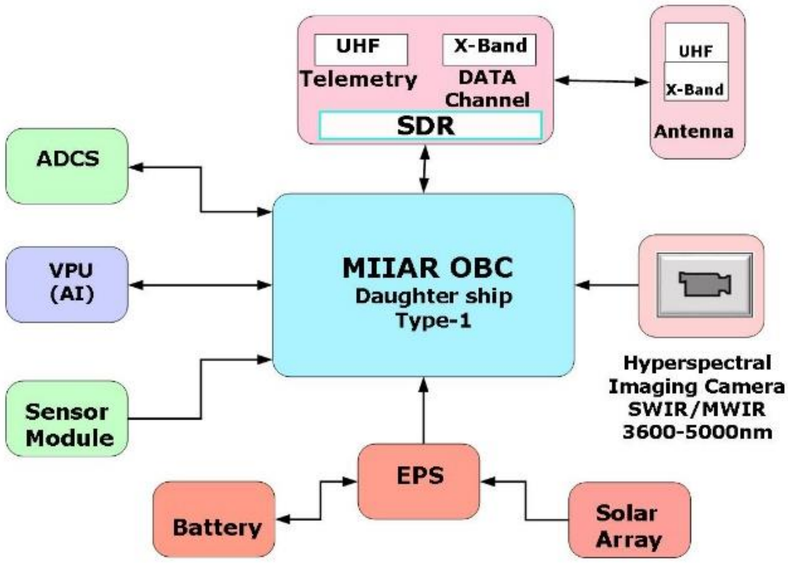

Figure 3. Block diagram for DS-Type I

may work as a good reference for communication module in Interplanetary CubeSat. However, we hope to be able to accommodate better and new options that are continuously being developed and tested for LEO missions and pushing the boundaries in terms capacity of COTS devices for small satellite. The MS-DRS satellites will be solely dedicated for data communication and different communication modes will be performed based on mission demands after proper analysis of appropriate schemes available in real time to get the best output possible. Moreover, it is quite new and heavily challenging idea to put a 12U CubeSat in an areo stationary orbit of Mars and keeping all three motherships alive and insync with the observational satellites while being monitored and controlled from Earth. The block diagram for MS-DRS is given on Figure 2.

3.2. Daughter Ship Type I (DS-I)

The DS-I is a pair of 6U CubeSats for advanced Mars observation mission that will provide high speed and continuous information and data from various observation studies through the high resolution VNIR Hyperspectral Imaging camera (400-1000nm), included as a payload [15]. It will consist of deployable UHF and X band antennas for simultaneous real time data communications to MS-DRS. The constellation will be fitted with a Software Defined Radio (SDR) for a complete freedom in frequency choosing for receiving or sending data to/from MS-DRS, which will provide real time data support from Earth for telemetry and other mission critical tasks. As for the OBC, we have decided to use a modified AiOBC design as described in [13]. As for handling Distributed Deep Learning, the CubeSat is fitted with an AI-on-the-edge device, a Visual Processing Unit (VPU) which will analyze the numerous observational data and will perform computation based on model parallelism. For station keeping, the CubeSat requires a micro propulsion system to correct the alignment and orbit for stable parking. We have chosen to include a reflective IR spectroscope as a payload. This device will be used to study and analyze the change in thin Martian atmosphere of a targeted area. As for power, the satellite will be powered by a deployable solar array of several solar cells, providing the required power, as used in the MarCO 6U CubeSat mission. The block diagram for DS-Type I is given on Figure 3.

3.3. Daughter Ship Type II (DS-II)

The DS-II is a pair of 6U CubeSats for advanced Mars observation mission that will provide high speed and continuous information and data from various observation studies through the thermal IR emission spectroscopy (5800-50000nm), included as a payload [15]. It will consist of deployable UHF and X band antennas for simultaneous real time data communications to MS-DRS. The constellation will be fitted with a Software Defined Radio (SDR) for a complete freedom in frequency choosing for receiving or sending data to/from MS-DRS, which will provide real time data support from Earth for telemetry and other mission critical tasks. As for the OBC, we have decided to use a modified AiOBC design as described in [13]. As for handling Distributed Deep Learning, the CubeSat is fitted with an AI-on-the-edge device, a Visual Processing Unit (VPU) which will analyze the numerous observational data and will perform computation based on model parallelism. For station keeping, the CubeSat requires a micro propulsion system to correct the alignment and orbit for stable parking. We have chosen to include a reflective IR spectroscope as a payload. This device will be used to study and analyze the change in thin Martian atmosphere of a targeted area. As for power, the

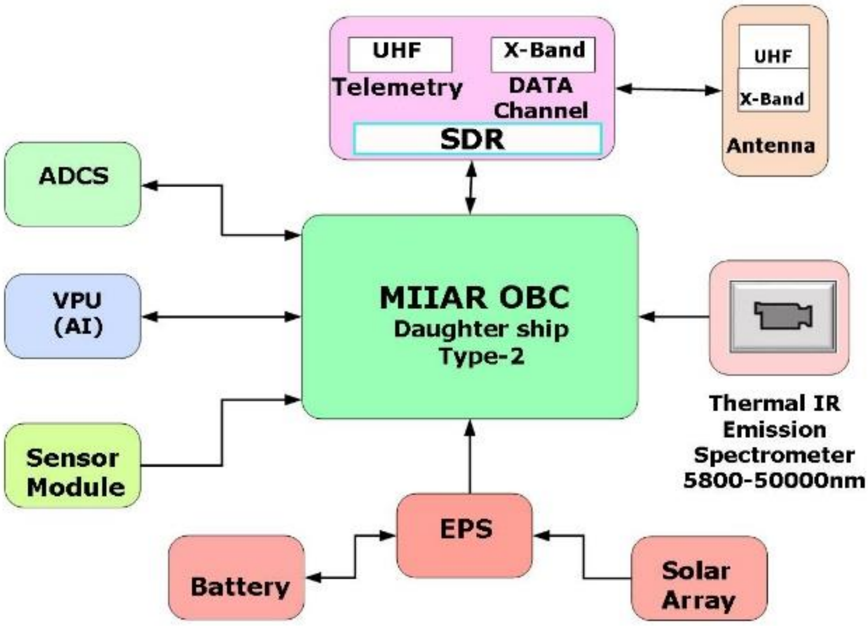

Figure 4. Block diagram for DS-Type II

satellite will be powered by a deployable solar array of 42 solar cells, providing approximately 35W of power, as used in the MarCO 6U CubeSat mission. The block diagram for DS-Type II is given on Figure 5.

4. Science goal and Science requirement

The overruling goals of the observational CubeSat set of MIIAR are to characterize the climate and weather of Mars focusing on the hydrological, CO_2 and dust cycles of the planet and to produce an accurate and precise 3d mapping of the surface of Mars. Our general approach is to generate a global data set as independent from models as possible and use it to develop an objective characterization of the Martian weather and climate system over the duration of the MIIAR mission. Two specialized scientific instruments, the Hyperspectral Imaging Camera and the Thermal IR Emission Imaging Spectrometer, contained in the observational Cube Sats will carry out this task. This in turn will allow us to evaluate and improve models of Martian climate and weather. Our intent is to create a complete scientific report of the planet's atmosphere and map of Mars, so that early human settlers and explorers to the planet can plan a definitive strategy for successful landing and colonization of Mars. The science objectives are given in Table 1.

Data attributes	Instrument type
High Resolution Imaging	Hyperspectral Imaging Camera
Daily global mapping	Hyperspectral Imaging Camera
Atmospheric water concentration	Thermal IR Emission Imaging Spectrometer
Relative humidity	Thermal IR Emission Imaging Spectrometer
Temperature	Thermal IR Emission Imaging Spectrometer
CO^2 density and bulk pressure versus height in atmosphere	Thermal IR Emission Imaging Spectrometer
Targeted Obs. & Multi-spectral Survey Emission Phase Functions	Thermal IR Emission Imaging Spectrometer
Dust and ice concentration on atmosphere	Thermal IR Emission Imaging Spectrometer

Simultaneous Communications relay in mixed frequency band	UHF,VHF, K, and X band
Experimental Optical relay Communications	Optical communication module
Trajectory control and management to keep the constellation working for Continuous and possible real time data relay	Micropropulsion, processing software, advanced engineering techniques for navigation, guidance, control

Table 1. Science objectives

As all the spacecraft are equipped with a low powered AI accelerator, we plan to implement three machine learning computation processes on the collected science data, for intelligent detection and computations onboard the space crafts. These are described below.

4.1. Classification and Analysis of Hyperspectral images using Distributed Deep Learning with data parallelism

As described in [16], one of the most important tasks in hyperspectral imaging is the classification of the pixels in the scene in order to produce thematic maps. This problem can be typically solved through machine learning techniques. In particular, deep learning algorithms have emerged in recent years as a suitable methodology to classify hyperspectral data. Moreover, the high dimensionality of hyperspectral data, together with the increasing availability of unlabeled samples, makes deep learning an appealing approach to process and interpret those data. However, the limited number of labeled samples often complicates the exploitation of supervised techniques. Indeed, in order to guarantee a suitable precision, a large number of labeled samples is normally required. This hurdle can be overcome by resorting to unsupervised classification algorithms. In particular, autoencoders can be used to analyze a hyperspectral image using only unlabeled data. However, the high data samples leads to prohibitive training times. In this regard, it is important to realize that the operations involved in autoencoders training are intrinsically parallel. As each of the CubeSats are equipped with a VPU for Deep Learning, therefore, we propose to implement an onboard distributed deep learning algorithm model based on data parallelism with high speed communication for parallel computation and joining of the computed data for successful transfer to Earth for further analysis and archive.

Using unsupervised classification on different data sets and parallel computing by each of the participating observational CubeSats on its own taken images, and then consolidated on a central node for successful transmission of the classified image data, as the method described in [23], a large number of images can be efficiently classified onboard the MIIAR before post analysis in Earth. This reduces the time needed for real time image classification, which, in the future, can be used for semi-autonomous navigation of satellites. The model process is shown below in the Fig.

4.2. Using Detection algorithm for geological landforms on Mars using Convolutional Neural Network (CNN)

As described and explained in [17], the large volume of high-resolution images acquired by the Mars Reconnaissance Orbiter has opened a new frontier for developing automated approaches to detecting landforms on the surface of Mars. However, most landform classifiers focus on crater detection, which represents only one of many geological landforms of scientific interest. In this process, we will use Convolutional Neural Networks (CNN) using the onboard VPU to detect both volcanic rootless cones (VRC) and transverse aeolian ridges (TAR).

According to [18], a rootless cone, also formerly called a pseudo crater, is a volcanic landform which resembles a true volcanic crater, but differs in that it is not an actual vent from which lava has erupted. They are characterised by the absence of any magma conduit which connects below the surface of a planet. Rootless cones are formed by steam explosions as flowing hot lava crosses over a wet surface, such as a swamp, a lake, or a pond. The explosive gases break through the lava surface in a manner similar to a phreatic eruption, and the tephra builds up crater-like forms which can appear very similar to real volcanic craters. Transverse aeolian ridges (TARs) are a type of sand ridge on Mars and are one of the most common landforms on Mars. They are mid-way in height between dunes and ripples; they are not well understood. One possible mechanism for their formation is that larger grains like pebbles are rolled on top of smaller ripples; then, finer dust settles into the cracks, making the TAR larger than typical ripples.

This system, named MarsNet, consists of five networks of CNN, each of which is trained to detect landforms of different sizes using the hyperspectral images taken by the DS constellation. The system would be executed on the MS-DRS in the Distributed Deep Learning platform, receiving images from the DS below and performing ML operations on the images onboard. By comparing the detection algorithm with a widely used method for image recognition, Support Vector Machines (SVMs) using Histogram of Oriented Gradients (HOG) features, the CNNs can detect a wide range of landforms and has better accuracy and recall in testing data than traditional classifiers based on SVMs. This would allow the system to automatically map the geological landforms onboard, using the above classifier, before sending the different parts of the completed map to Earth.

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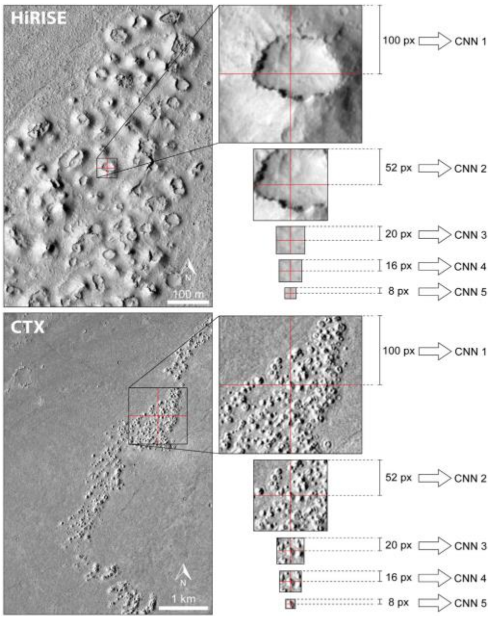


Figure 5. Top: Section of HiRISE image PSP_002292_1875 along with VRC training samples extracted at the different sizes for each of the CNNs in the MarsNet architecture. All the images are centered in the same feature, and five images sizes are created out of each target, each of the images feeds one of the five different ConvNets in MarsNet. Each image is segmented in four sub-images. Bottom: Target examples from a section of CTX image P03_002147_1865. Both images are illuminated from the left. [18]

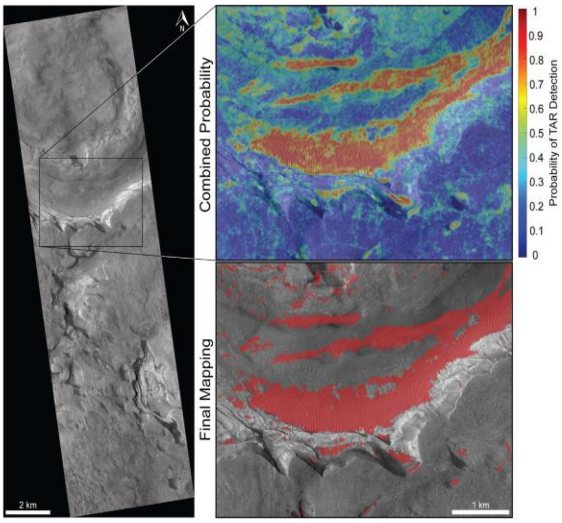


Figure 6. Left: HiRISE image ESP_020889_1320, includes a large number of TARs along with bedrock and sand. Upper Right: Probability of TAR detection using MarsNet after combining the results of its five classifiers. Lower Right: Final mapping of TARs (shown in red) based on a detection threshold of 0.5. [18]

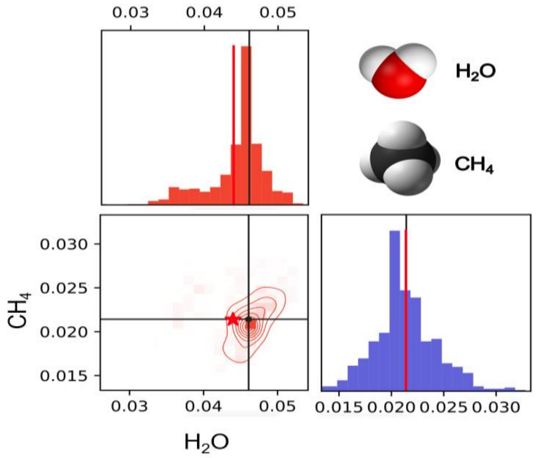
4.3. Machine Learning based Atmospheric Data Retrieval Framework

According to [18], over the past decade, the study of extrasolar planets has evolved rapidly from plain detection and identification to comprehensive categorization and characterization of exoplanet systems and their atmospheres. Atmospheric retrieval, the inverse modeling technique used to determine an exoplanetary atmosphere's temperature structure and composition from an observed spectrum, is both time-consuming and compute-intensive, requiring complex algorithms that compare thousands to millions of atmospheric models to the observational data to find the most probable values and associated uncertainties for each model parameter. For rocky, terrestrial planets, the retrieved atmospheric composition data can give insight into the surface fluxes of gaseous species necessary to maintain the stability of that atmosphere, which may in turn provide insight into the geological and/or biological processes active on Mars. These atmospheres contain many molecules and chemicals, such as H_2O, CO_2, O_2, N_2 & CH_4. Some of them bio signatures, spectral fingerprints indicative of biological activity, if any, which will become observable with the next generation of telescopes. Runtimes of traditional retrieval models scale with the number of model parameters, so as more species that are molecular are considered, runtimes can become prohibitively long. Recent advances in low powered machine learning (ML) and computer vision accelerators offer new ways to reduce the time to perform a retrieval by orders of magnitude, given a sufficient data set to train with in real time.

According to [19], general objective of an Information Retrieval system is to rank relevant items much higher than non-relevant. To do it, the items must be scored using a *Retrieval function* i.e. a scoring function that is used to rank data in vast unstructured data. The function is based on a retrieval model that defines the notion of relevance and makes it possible to rank the documents or data.

Similarly, the above system comprises of an ML-based retrieval framework called Intelligent exoplaNet Atmospheric RetrievAl (INARA) that consists of a Bayesian deep learning model for retrieval and a data set of 3,000,000 synthetic rocky exoplanetary spectra generated using the NASA Planetary Spectrum Generator (PSG). It is a ML retrieval model for rocky, terrestrial planets such as Mars and the first synthetic data set of terrestrial spectra that can be generated at this scale.

The framework would be pre-trained using supervised learning and tested onboard the MS after receiving the atmospheric data from the DS constellation, using the onboard VPU and the Distributed Deep Learning platform. The resulting ranking of atmospheric data would be computed and sent back to Earth in order of importance and target data according to the computed ranking by the retrieval system. This method would save valuable data bandwidth as no unnecessary or low priority data would be sent to Earth, making the observational aspect of the mission very efficient.



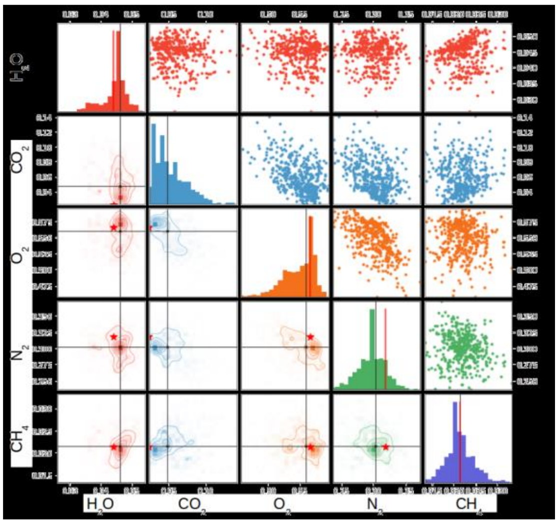


Figure 7. Predictions of H2O, CO2, O2, N2, CH4 based on the best performing model; training limited to 64 epochs on 110,000 parameter–spectra pairs hence some uncertainties reflect calibration issues. [18]

5. Orbital Analysis and Recommendation

For the above-mentioned sets of CubeSats, two types of orbits will be used for deployment. This is because different types of observational instruments, such as nadir and limb scanning instruments, requires different orbits for precise and continuous data gathering, as mentioned in [20]. The data relay sets of CubeSats will be deployed to an aero-stationary orbit of Mars for maximum range and minimum gap for continuous communication to Earth, while the observational set of CubeSats will be deployed into a high inclination orbit of Mars.

5.1. High Inclination orbit of Mars

Many atmospheric sounders like PMIRR (aboard Mars Observer and Mars Climate Orbiter), MCS (aboard the Mars Reconnaissance Orbiter), or MAMBO (initially planned for the CNES Mars Premier Orbiter) are designed to directly scan the atmosphere at the limb, which corresponds to an angle of 90°. As mentioned above, to reach their scientific objectives, such instruments have to observe the Polar Regions, which our observational CubeSats carry. It is very instructive to compare these results with the sampling obtained by a similar instrument performing across track limb scanning aboard a Sun-synchronous satellite. In the temporal term, the sampling is very poor, and in spatial term, no latitudes higher than 70 degree are observed.

Circular orbits are often used in Martian missions, but not always.

For elliptic orbits with a low eccentricity e (e<0.2) the precession motion is about the same as in the case of a circular orbit. For example, for Mars Reconnaissance Orbiter (MRO), a=3681:251 km,
ha = 312:5 km (apoapsis), hp = 257:6 km (periapsis),
e =0:007455, thus F =1:00011, representing a relative correction of 10−4.

Orbits with high eccentricity (e>0.2), pose other problems that are out of the scope of this paper. With such orbits, the altitude and the velocity of the spacecraft (and thus the conditions of observations) are significantly different at apoapsis and periapsis. The Mars Express mission provide a recent example of such an orbit. In most cases, a hemisphere (north or south) is favored depending on the latitude of the periapsis, which itself varies with a secular motion (apsidal precession), except for orbit close to the critical inclination (i=63◦ or 117◦). Obviously, such orbits are not ideal to monitor the atmosphere with a good spatial and temporal sampling.

5.2. Aero-stationary orbit of Mars

A significant part of the MIIAR is to provide continuous real time communication from/to Earth for the observational sets of CubeSats, such as scientific data uploads and telemetry control. Such missions usually use relay orbiters to communicate with the Earth, and the choice of orbit for future spacecraft should be consistent with a relay function (as it was the case for Mars Observer, Mars Global Surveyor, Mars Odyssey, Mars Express or Mars Reconnaissance Orbiter).

An aero stationary orbit is a circular aero synchronous orbit in the Martian equatorial plane about 17,000 km (11,000 mi) above the surface, any point on which revolves about Mars in the same direction and with the same period as the Martian surface. Aero stationary orbit is a concept similar to Earth's geo-stationary orbit. It about 3,000 kilometers inside the orbit of Deimos, one of Martian Moon. Any satellites in aero stationary orbit will likely suffer from increased orbital station keeping costs, because the Clarke belt of Mars lies between the orbits of the planet's two natural satellites. Phobos has a semi-major axis of 9,376 km, and Deimos has a semi-major axis of 23,463 km. The close proximity to Phobos in particular (the larger of the two moons) will cause unwanted orbital resonance effects that will gradually shift the orbit of aero stationary satellites. Therefore, it will require some maneuvers for station keeping.

In theory, non-Sun-synchronous orbit are not ideal for this purpose since they will inevitably go through “dawn-dusk” phases during which the available solar power for surface modules will be low when communication will be possible. However, since we tend to select orbit with high precession cycle, the problem should be only significant for periods a few sols (but several times per year).

Since the duration of the contact between the sets of observational and the relay CubeSats is only a few minutes for low circular orbits, communication should be achievable using batteries.

A more serious issue is that the interval between each contacts should be short enough to command the lander and download the data on a regular basis. Three sols is usually considered the minimum acceptable. Assuming that a suitable contact is ensured if the satellite (as seen by the Lander) is at least 45◦ above the horizon, it happens that the problem is exactly similar to the one addressed above in Section 6 (our goal there was to observe every point at least every 3 sols and with a viewing angle of less than 45◦).

Therefore, one can show that the optimal orbit altitude must be chosen outside the forbidden zone corresponding to the resonances, as shown in the below table.

Forbidden zones		Inclination *i* (deg)							
Altitude	Resonance	55	60	65	70	75	80	85	*S-s*
Z_S	..11:1	738	741	744	747	751	755	760	769
Z_R		701	703	707	711	715	719	724	733
Z_i		665	668	671	675	679	683	688	697
Z_S	..12:1	508	512	516	520	524	529	534	543
Z_R		463	467	471	475	479	484	490	499
Z_i		420	423	427	431	436	441	447	456
Z_S	..13:1	305	309	313	318	323	329	335	344
Z_R		255	259	264	269	274	280	286	296
Z_i		207	211	216	221	227	233	239	249

Table 2. Forbidden altitude for different inclination in Mars satellite orbit selection. Forbidden altitude zones correspond to the range of satellite altitude that provide insufficient longitudinal sampling for circular orbit. *S-s* (sun synchronous)

After reviewing the different orbits around Mars in [], we have come to the conclusion that the point with the longitude -18.138 degree can be used as the initial condition for areostationary orbits, where station keeping is not necessary.

6. Communication module

The constellation in the MIIAR mission consists of two specialized communication modules. The first is for sending and receiving data between the relay satellites i.e MS-DRS. This module would be used to implement Distributed Deep Learning computations and to provide vital telemetry commands to the observational CubeSat sets i.e DS-I and II. The other module is for continuous communication from/to Earth through intermediatory satellites for uploading of important scientific data and for receiving key telemetry commands for the entire constellation.

6.1. Inter-satellite optical communication module

Optical communication in space opens virtually unlimited capacities without regulations. By using lasers, satellite optical communication has a readily available frequency band and can transmit with higher power efficiency and with smaller and lighter terminals. Thus, it is expected to be a key technology to support the future satellite communication. For a given mass, power consumption and volume, laser communications can offer an increase in bandwidth over classical RF technology allowing for a variety of new options.

Laser links have been so far attempted by large satellites but the future presents a clear trend of satellite miniaturization (less than 10 kg) or even smaller down to 1kg satellites typically in the form of CubeSats.

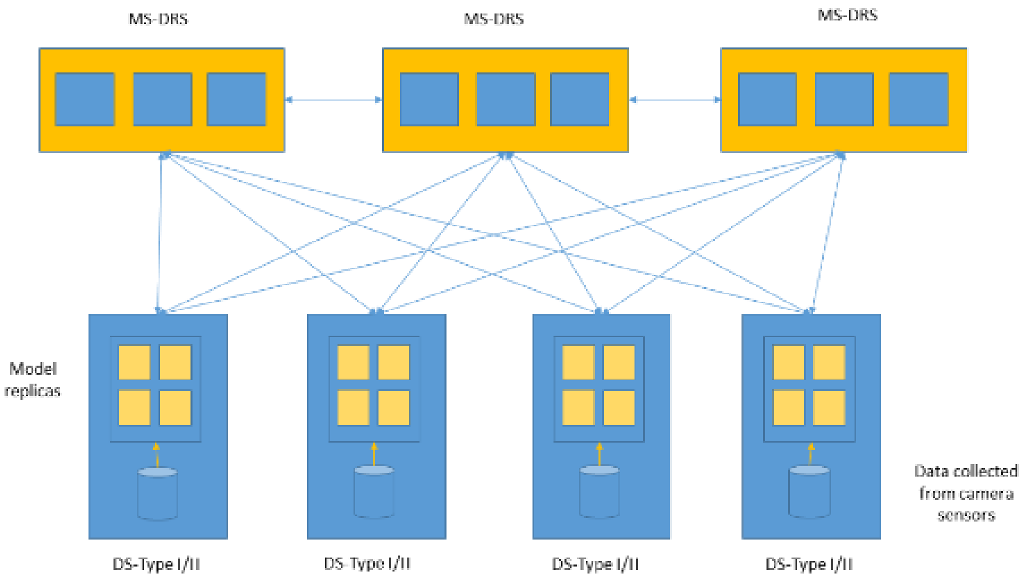


Figure 8. Distributed Deep Learning platform scheme

Despite their limited volume and power, CubeSats can compete with the largest satellites.

Today many companies are planning and experimenting to establish data communication network between CubeSats. Although, there is still no commercial COS optical communication module, some modules are already being tested by the ESA and NASA to measure and study the feasibility of such modules.

Therefore, after careful consideration and study of various experimental and proposed optical inter-satellite link, we have prepared some guidelines and recommendations that will help us in the future to finally implement this type of modules in MIIAR. They are:-

- The range of the optical link should be greater than 30,000 km
- The weight of the module should be no more than 15kg.
- The dimension or size of the module should be within a standard 3U CubeSat.

We believe, after following these guidelines, we will be able to effectively implement an inter-satellite communication link between the data relay CubeSats.

6.2 Deep space communication module

According to [21], satellite communications was born in the late 1950s with the successful launch of SPUTNIK-1. Since then, satellites have become a major component in today's world communication infrastructure. Similarly, satellites are an essential part of space exploration such as inter-planetary exploration, be it lunar habitation, asteroid mining, Mars colonization or planetary science/mapping missions of the solar system. Communication from/to the Earth is largely required for precise telemetry command for successful completion of missions and for sending of valuable data for future study and research of the data captured by the exploration satellites.

In our deep space communication module, we have decided to equip it with a SDR, which will be capable of transmitting and receiving Ka band RF waves, which has much greater bandwidth with minimum interference and error. It would be relayed through the present Deep Space communication networks by ESA, NASA and other space agencies to Earth. Antennas supporting Ka bands will be fitted into the MS-DS sets of data relay satellites for continuous and reliable communication.

7. Proposed implementation of Distributed Deep Learning in the constellation

As shown on Figure 10, to implement Distributed Deep Learning in the MIIAR constellation, we need to first partition the data and divide them among the workers i.e. the Daughter Ships (DS-Type I & II). Since each DS will gather hyperspectral image & various atmospheric data from its sensors of Mars, the data is initially segregated. After the data is acquired, each DS will perform the ML computations, as mentioned on Section 4 on their respective data. The onboard low powered AI accelerator of each DS CubeSat in the constellation would complete the ML computations. Since we have multiple DS scanning the data in parallel, we should be able to scan more data than when using a single node. This increases throughput through distributed parallel computing. We let each DS perform

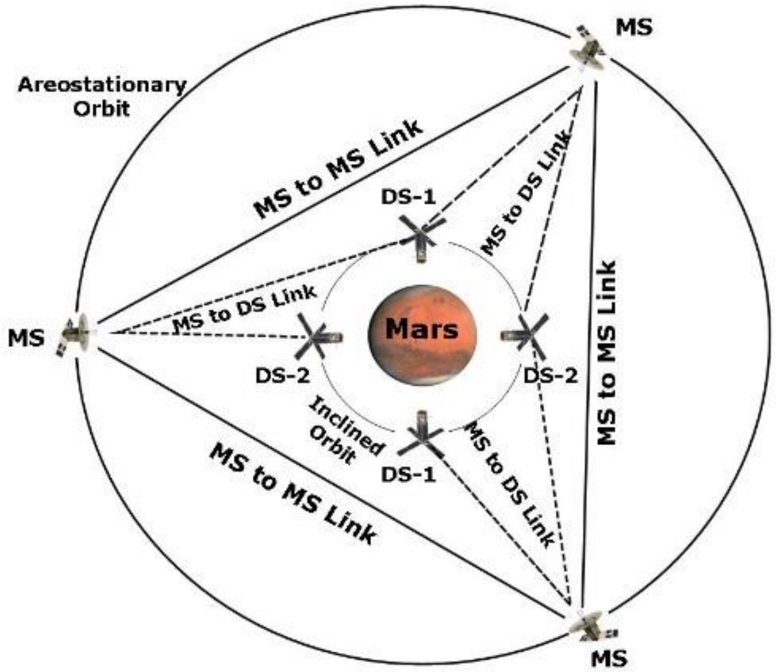


Figure 9. System overview of MIIAR constellation

the training on its own data and generate a set of parameter updates.

After the generation of parameters, the DS clusters synchronize their parameter states by inter-satellite communication links, until they reach a consensus. The three MS-DRS clusters would act as the server to this network. After the synchronization is complete, and the parameters are initialized, the MS-DRS would establish connection to Earth and start transferring data.

Implementing the Distributed Deep Learning platform on-board the satellite constellation improves the ML computation capabilities of the satellites by a factor of the number of satellites. This reduces the time needed for ML computation significantly and in the future, enable the satellite to function autonomously, without communication from Earth.

8. Concept of operations

The primary mission of MIIAR is to successfully carry out the sub-missions assigned to it in its targeted life time by returning spectrally resolved images of target locations of Mars, measure and study the different atmospheric conditions and environments of Mars as well as processing and training the distributed deep learning models. In order to do so, the observational sets of CubeSats i.e DS-I and II will be launched in a high-inclination orbit. As for the data relay sets, these will be launched into an aero-stationary orbit of Mars for continuous communication between the observational CubeSats and Earth. It would also receive computed data from Distributed Deep Learning models from the daughter CubeSats and join them for sending to Earth.

Until deployment, all the Satellites under MIIAR will remain in the power-down state per CubeSat requirements. Power-on will occur upon deployment from the secondary deployer. Per CubeSat specifications, MIIAR will not execute maneuvers until 30 minutes after deployment, though solar panel voltages will be logged and sensor data will be recorded during this period. After 30 minutes, the flight computer will initiate system checks to ascertain stored energy and thermal environment parameters. If within bounds, the main flight computer will initiate de-tumble operations. De-tumble will last for approximately one orbit and will result in the X & Ka band antenna, UHF antenna and two camera units in the line-scanning orientation.

Subsequent to de-tumble, all clusters of MIIAR will enter an idle mode in which only minimal station keeping operations are active to log temperature and subsystem data, to charge batteries, and to maintain a nadir orientation for the camera and X & Ka band antenna. During this period, based on data from the onboard star tracker, the main computer will calculate the timing for the next pass over a pre-determined ground or relay station. When in range of a data relay satellite of the constellation, the flight computer of MS-DRS will power on the Ka-Band Communication system and begin transmission of station-keeping (thermal, power, orientation, subsystem status) and dynamical (orbital position, velocity) data.

Given a successful downlink of initial station-keeping data and an internal "PASS" on subsystem checks, the MIIAR observational set of CubeSat will begin its various science sub-missions. During the science phase, the observational CubeSats will continue to monitor power and subsystem status, maintain pointing orientation, and monitor proximity to the relay satellites. In addition, the main computer will compare longitude and latitude of Mars with a list of stored image targets for image acquisition. When an image target is in daylight and on the orbital track and when power and subsystem status is conducive to camera operations, the DS-I and II camera and IR spectroscope will be brought into standby mode and location data will be logged until the predetermined image acquisition coordinates when the camera will be activated. In case of nighttime, the IR thermal emission spectroscope will be activated and start to acquire data. The cameras will acquire data until the predetermined image track coordinates are reached and the cameras will be returned to standby mode as the image data is processed for storage on the flight computer's storage. After image transfer, the camera and spectroscope will be powered down. To use SDR, the DS-I and II will switch to a SDR mode which will disable the primary communication module and activate the SDR for data transfer and measurement of data metrics to the MS-DRS. Lastly, to activate and train models using the Deep Neural Network module, an additional Data training mode is available and can be manually or automatically activated, when it is required.

As the observational CubeSats return to a low-power state, the main computer will calculate the next pass under the range of the relay satellite and prepare for data downlink. At the next pass of a range of the data relay satellite, the main computer will activate the communication system and downlink the camera data. The cluster of the data relay satellites are equipped with an inter-satellite optical link, by which it will share the data received from all of the daughter satellites among each other and perform deep learning computations before joining them into multiple sets. Then, the multiple sets of computed data will be sent to Earth through the Deep Space communication module.

In case of emergency and failure of any subsystems, the CubeSats in the MIIAR constellation will switch to Recovery mode and will check all the subsystems for error. Upon finding the error, the main flight computer will initiate appropriate actions based on the pre-programmed instructions to return to idle mode. As for shortages of power, the MIIAR constellation will suspend all operations and switch to idle mode for full charging of battery. After a full recharge, the constellation will resume operations and switch back to idle mode for the continuation of its science missions.

9. Conclusion

We have imagined an inter-planetary Mars observation mission with compact payload package comprising of hyperspectral imaging capability with on board Distributed Deep Learning capabilities in a 6U and 12U CubeSat constellation. The payloads cover multiple criteria on remote sensing and deep learning applications and are aimed to study and research never-before-seen innovations and ideas in smaller platforms for planetary exploration and observation. In our mission, we have introduced a number of new and innovative ideas including using two scientific instruments such as a Hyperspectral Camera and a IR emission spectroscope in a 6U satellite for reliable remote sensing and planetary observation of Mars's atmosphere and surface. Software defined radio in CubeSat as a backup or as an emergency recovery system in a Micro or CubeSat's Communication sub-system is an important criterion for our study. The configurational advantages of SDR can be used to study and conduct specialized experiments, which later will be useful for such payload systems in next generation satellite network operations like formation flying, constellation design and spacecraft docking/undocking. As proposed, use of an on-board deep neural computing & machine learning module to perform Distributed Deep Learning computations for analysing and processing the Multispectral images and atmospheric data taken by the satellite will add extra dimensions in future planetary observational missions. Innovative doors remain unexplored in terms of AI based control of all the fundamental subsystems of micro and Nano satellites. With the applications of machine learning and distributed computing over a constellation in mind, our goal is to enrich the payload system with continuous improvement and training in search of a qualified neural algorithm for autonomous/semi-autonomous satellite system for micro and Nano satellite platform.

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