Human-integrated Multi-Agent Exploration using Semantic Communication and Extended Reality Simulation

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***Abstract*—In hazardous or inhospitable environments such as Mars, exploration and maintenance tasks pose high risks to human operators. Hence, the assistance of mobile robotic systems is required. One of the main applications of outdoor exploration is resource localization. This scenario imposes several challenges: Resources to be found are scarce, and their distribution is unknown. Further, we have limited processing power. Dangerous situations require fast decisions, and thus minimal processing and communication latency. Lastly, the huge amount of information received from the rovers can become quite difficult to interpret by the human operators. To cope with these challenges, we introduce a conceptual framework for the integration of humans with a multi-agent system in the planetary exploration context. The scenario in consideration is that of human-integrated multi-robotic exploration by a team on Mars consisting of rovers and a few astronauts for outdoor sampling and remote operation from within an extraterrestrial habitat. The rover team adapts its behavior to the status of the communication, and with semantic communication, we convey the meaning of the desired exploration data into the data transmission. Then, based on the received semantic information, we visualize the information to provide humans relevant information for decision-making. In order to implement the common framework in a virtual scenario, we combine a human-in-the-loop simulation in extended reality with a rover simulation environment.**

***Index Terms*—Exploration, extended reality, human-machine interface, multi-agent, semantic communication**

I. INTRODUCTION

Advancements in science and technology have transformed humankind from a mere species living on the Earth to one that impacts both our Blue Planet and beyond. However, major developments in human habitats and betterment in the quality of life have depleted our resources extensively, taking us further away from a sustainable existence. Extraterrestrial exploration has been of immense importance since decades, aiming to answer several fundamental scientific questions such as the formation of the universe, evolution and alien life. Space robotics has taken a leap in the 21st century with multiple unmanned missions launched to explore the Moon, Mars, and outer space. Future space missions will involve hybrid teams of humans and robots carrying out scientific sampling and experiments in collaboration with each other, to pave the way for extraterrestrial settlements consisting of conducive habitats for human survival. This entails cooperation between different autonomous systems, communication of essential information between robots and humans, and clear representation of this information to make it human-understandable.

Planetary robotic missions involve a variety of scenarios, including resource localization, geological discovery, exploring unknown space and moreover Search And Rescue (SAR) during missions with bigger teams of astronauts and robots. Such applications pose grave challenges arising due to various static and dynamic variables. Hardware resources are limited and expensive. The robots must be designed to use available energy efficiently, especially for night survival [1]. Prior knowledge of the environment is often limited. Extreme terrain, mission criticality and environmental phenomena like dust storms are bound to pose locomotion perturbations, sensory obstructions and possibly loss of functionality or members. Unreliable communication with loss and latency affects information transfer, team coordination and in turn the overall mission success. Lastly, the huge amount of information received from the robots can become very difficult to interpret by the human operators. It is therefore necessary to take these factors into consideration during the planning and execution phases of the mission.

To tackle these challenges, this work is a step towards human-integrated multi-robotic exploration. We develop an integrative architecture that brings together humans, robots, and semantic communication within one mathematical framework, that we will evaluate using a proof-of-concept demonstration. The mission scenario is a human habitat with a human operator in a Mars-like terrain. A team of human explorers and rovers

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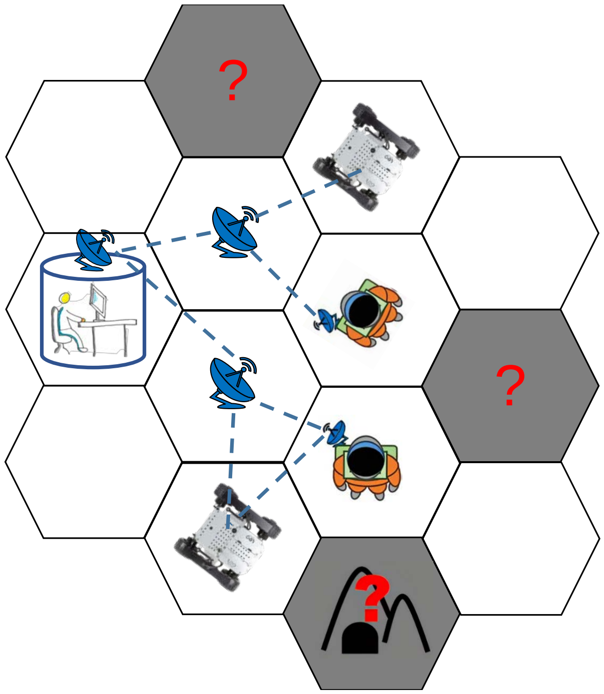

Fig. 1. Example Scenario of the Multi-Agent System (MAS) in action.

explore the environment and information is shared between the agents as shown in Fig. 1:

1) The human-rover team is responsible for exploring the environment for regions of interest.
2) The rovers can revert to the human explorers and human operator with relevant information. Interaction is achieved through semantic communication [2].
3) The human operator can then visualize this information for interpretation and decision-making.

The proposed framework combines exploration, communication and human-robot interaction, and serves as a test bed for further experiments in the domain of human-integrated multi-agent exploration.

II. Related Work

A. Exploration

Mission planning and task allocation are essential for efficient and collaborative exploration. Depending on the final goal criteria, several algorithms have been proposed for multi-robot coordination. For examples in various application domains, see the review [3] on multi-robot systems. With respect to space robotics, [4] and [5] summarize the advances in cooperative robots used in space missions. MOONWALK [6] is a project targeting scenarios that involve human-robot cooperation on Moon and Mars missions.

A number of multi-robot coordination and navigation algorithms have been developed in recent years, including Particle Swarm Optimization (PSO) [7] and Bayesian optimization models such as the one in [8]. The early extensive work [9] covers the entire spectrum of bio-inspired multi-robot and swarm navigation. The authors of [10] propose a threshold-based clutter field assessment model for autonomous multi-robot navigation used in search missions. Online fleet coordination and dynamic formation control have been discussed in [11] and [12]. Distributed multi-robot exploration [13] integrated with simultaneous mapping has been widely investigated in works such as [14] and [15]. In [16], the authors consider communication constraints during mission planning and task execution supervised by human operators with a set of predefined tasks. Exploration has been mostly treated as merely an optimal path planning problem. Intelligent strategies to tackle temporary separation of one or more members from the rest of the team, in areas like caves and lava tubes, are often missing.

B. Semantic Communication

An integral part of remote exploration missions—in particular in space—is wireless communication: It allows the humans and robots to move freely and to communicate over large distances. Nowadays, the communication systems aim at error-free digital communication and already operate near its theoretical limit [17].

But resources are scarce in both space with strict power and latency constraints and on earth with future 6G systems serving diverse applications such as autonomous driving and Extended Reality (XR). This calls for a paradigm shift from digital agnostic transmission to application-aware, i.e., semantic, communication [2], [17]–[19].

Semantic communication, as demonstrated in [2], is illustrated by a biologist using an image sensor to capture data about a tree's botanical features. Rather than focusing on raw data, the biologist seeks the meaning, such as the tree's class or health assessment. This example highlights that the interpretation of identical sensed data can vary among different entities, like humans or specific tasks, based on context. For instance, a child may be concerned with whether the tree is climbable or provides shade. In both cases, the goal is to communicate only relevant semantics, discarding unnecessary information to conserve bandwidth, power, and reduce latency. In comparison, classic digital communications aims to transmit the raw image data.

Semantic communication is an evolving area with numerous research inquiries yet to be addressed. The authors of [20] were pioneers in delineating sources and channels of semantic information, aiming to address semantic design using traditional methodologies [17]. Prompted by the works of Shannon [17], Bao et al. [20], and renewed research interest in Machine Learning (ML) techniques for communications, transformer-based Deep Neural Networks (DNNs) have been introduced to Auto Encoders (AEs) for the transmission of text and speech. This integration aims to acquire compressed hidden representations of semantic content, enhancing communication efficiency, particularly in scenarios with low Signal-to-Noise Ratio (SNR) [21]–[24]. For a comprehensive exploration of semantic communication within a broader scope, readers are directed to delve into the surveys presented in [18], [19].

C. Human Machine Interface

The integration of humans as agents in an exploration-oriented robot team is a multi-stage process that involves data processing and visualization for humans, data interpretation and decision-making by humans, as well as collaborative decision-making. Visualization technologies from the field of game design can be utilized to model an immersive and interactive simulation environment. Visualizing large amounts of data in a XR environment can be achieved by focusing on relevant data within the human field of view [25]. Time-dependent scalar and vector fields in the form of a navigable 3D XR film enable the exploratory examination of data [26]. Real-time data synchronization in XR can be used for collaborative decision-making [27].

Currently, many different approaches exist for the teleoperation of industrial robotics, mainly based on the combination of Robot Operation System (ROS) and visualization technologies. Peppoloni et al. introduced an innovative interface integrated with ROS, enabling remote robot control through hand gestures. Their study highlights ROS's capability in immersive teleoperation experiences [28]. Baklouti et al. suggested an enhancement to ROS-controlled teleoperation of Yaskawa robots, integrating ROS control with Gazebo simulation to improve the safety measures during teleoperation tasks [29]. Naceri et al. introduced a concept for a ROS-compatible robotic platforms with high-performance XR interfaces for teleoperation. This initiative showcases the potential synergy between ROS and VR technologies, enhancing the overall teleoperation experience [30]. Garcia-Garcia et al. devised a teleoperation system for an assistive robot, employing a Kinect V2 sensor, Meta Quest VR glasses, and Nintendo Switch controllers. Their implementation utilized the ROS framework for seamless communication among these devices [31]. In summary, the related work in this field demonstrates the potential of interfaces between a robot simulation tool and visualization. The novelty of the approach presented in this paper is the design of an integrative framework for human-robot teams focused on exploration.

D. Existing Integrative Approaches

There already exist a few integrative frameworks. One is the joint learning and communication framework for multi-agent reinforcement learning over noisy channels from [32]. There, the authors propose to jointly optimize collaboration and communication between a scout and a guide with Deep Q-Learning and deep deterministic policy gradient. Both aim to find a treasure in a 2D grid and need to avoid obstacles. The scout can take actions on the environment but cannot observe the environment state, and the guide vice versa. Thus, the guide communicates over a noisy communication channel to the scout to control it remotely.

Another example is the ever-growing Metaverse, where users represented by avatars interact in a 3D virtual environment on the internet. The high resolution data requires efficient communication and intelligent content generation: Hence, in [33], the authors introduce a consolidated framework that seamlessly integrates semantic communication with AI-generated content. This framework facilitates the transfer of semantic information from user inputs, the creation of digital content, and the rendering of graphics within the Metaverse, ensuring the preservation of the original meanings.

This means exploration and communication as well as communication and visualization of created content were investigated, but just a few works like the mentioned ones do exist to the best of our knowledge.

In this paper, we aim to provide a pioneering contribution. Our work distinguishes by the two mentioned works fundamentally

- by combining exploration, communication and Human-Machine Interface (HMI).
- by considering a more detailed scenario, akin to the real-world.
- by an interdisciplinary approach making use of the respective expert knowledge.

III. Proposed Integrative Framework

The following are the scientific goals of this work:

1) Designing and implementing a multi-robot exploration strategy for a robotic team
2) Conveying desired meaning into the data transmission—Semantic communications (post-Shannon)
3) Visualizing exploration scenarios to provide humans with the semantic information for decision-making—Multidimensional visualization models
4) Integrating the information processing of 2. and 3. with exploration and navigation—Mutually-aware exploration and communication, provide relevant navigation and exploration information
5) Linking the technology designs to human decision-making—Developing a mathematical framework to connect intelligence

We propose to achieve these goals by the following integrative simulation framework shown in Fig. 2: We differentiate between four roles including Human Operator, Database, Human Explorer and Rover. The Human Operator is shown all data relevant for the mission via a graphical user interface. This includes the data of the Human Explorer as well as the data of the rover. A database is chosen as the common interface, in which all relevant tasks, position data and environmental conditions relevant to the mission are stored. The Human Explorer can be simulated via a VR environment. He/She is responsible for performing the actual tasks at the RoI. The rover will be integrated via the RoCK [34] framework. This can be both a software and a hardware-in-the-loop implementation.

At the beginning of the task allocation stage, tasks are available which are defined by the human operator and stored in the database. If the rover or human operator requests a new task, it is provided by the database as a pull system and the exploration stage begins. During the exploration, the individual actors are in constant communication with each

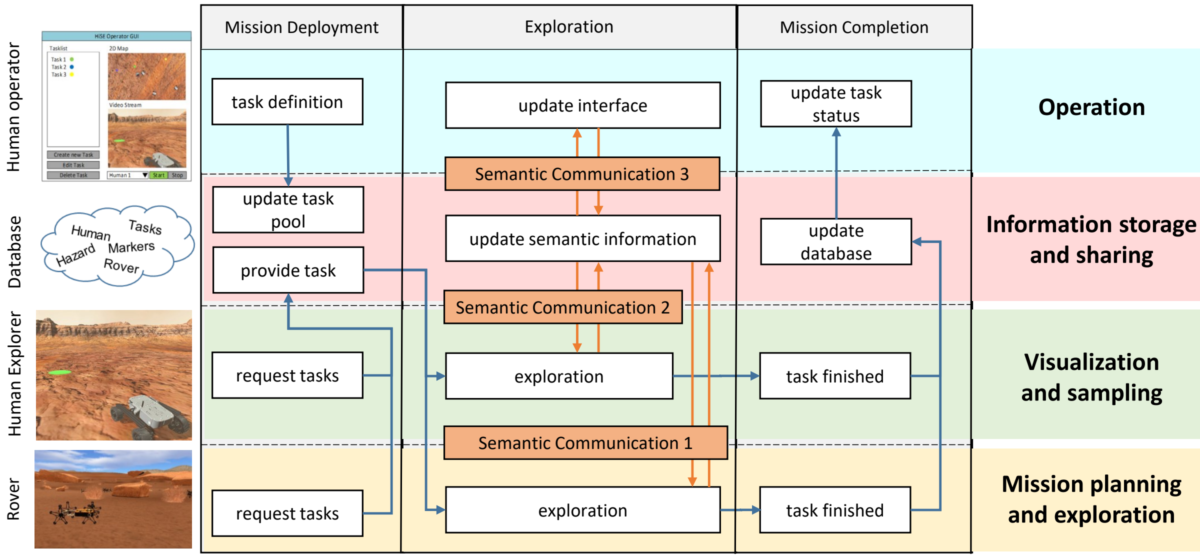

Fig. 2. Joint framework combining multi-agent exploration, semantic communication and visualization. The human operator defines tasks that are allocated to the human explorer and the rovers. During exploration, all members communicate the meaning via semantic communication.

other. Based on the semantic communication approach, only semantic information relevant to the mission is passed on. The information sharing includes a periodic update of the database and the status of the agents in the GUI of the human operator. When a task is completed, this is reported back to the database by human explorer or rover. A new task can be requested by any idle team member.

Thus, our integrative framework will connect human agents with intelligent MAS to accomplish exploration missions in an efficient, collaborative, and situation-aware manner. This architecture thereby enhances the autonomous capabilities of the MAS while incorporating humans into the decision-making process.

In order to develop the proposed framework, we will integrate three domains discussed in this work, i.e., robotics, semantic communication, visualization, and their respective approaches into one coherent system. In the following sections, we outline the contributions of each domain.

A. *Multi-Robot Exploration*

The mobile robotic network is tasked with exploration missions in pursuit of regions of scientific interest. The exploration team searches a given terrain for a set of predefined items of interest for scientific sampling. Such a Multi-Agent System (MAS) will incorporate a distributed intelligence paradigm, while having shared knowledge, and characterize a common-goal-oriented behavior. Each agent is capable of dynamically making decisions based on its state and that of the team, in a situation-aware manner [35], while communicating essential information to the astronauts. Decentralized decision-making is beneficial when managing larger robotic teams by reducing communication overhead. It also increases the system's flexibility to situational changes, and its resilience to faults and failure. Moreover, distributing control across rovers helps them to learn and improve their predictive power over time [35]. In this way, the shift towards a more decentralized approach is key to achieving greater scalability and transferability of the system. However, this approach brings along its own challenges like distribution of authority, information abstraction and security risks. Collective intelligence and shared models enable the robots to bootstrap their relevance in diverse scenarios.

Task allocation from the knowledge server takes place through auctioning [36]. Task-switching between rovers could take place during the mission depending on feasibility. The rovers follow an ROI-based approach. The rover's interest in exploring a particular region is a function of the knowledge it has acquired from exploration so far, elapsed time, and the rover's position with respect to other rovers and the environment. Rover status, explored area, ROIs discovered, are some of the data that are shared by the rovers. This information may not always be available, or sometimes partial, and often not up to date.

Fig. 3 depicts what happens at the individual rover level. The goal criteria are provided by the human operator via the shared knowledge server. The semantic communication module is explained in the following section. We will use probabilistic decision-making and a predictive model to compute target paths for each of the rovers with partially available information. This is performed within the Decision-Making layer. A combination of optimizers like frontier-based PSO [37] and Bayesian optimization techniques [14], [38] is suggested for task assignment along with a probabilistic cost function.

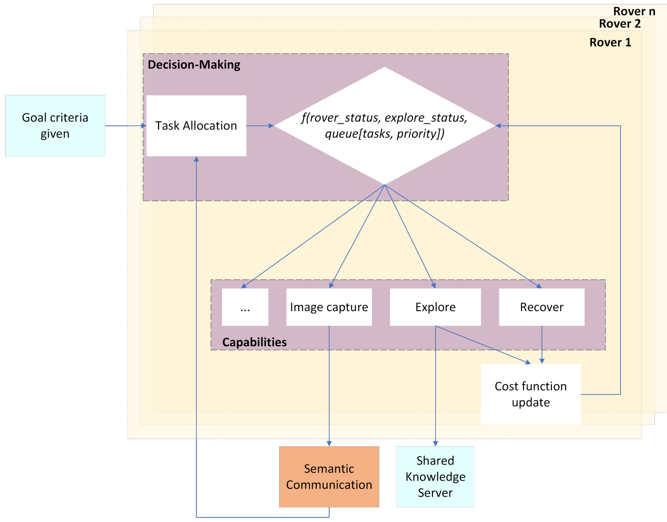

Fig. 3. Schematic diagram of the exploration module on an individual rover.

Predicting where each agent must explore next, based on agent status, information from prior exploration and communication status. The rover is equipped with (but not limited to) three types of capabilities, namely, Explore, Image Capture and Recover.

The exploration strategy of each rover is defined by a function, $\mathbf{Exp_{fn}}()$ that takes the following dynamic input:

- $\mathbf{rover\_status}()$, defined by the current status of the rover (idle, busy(task_ID, ($\mathbf{explore}|\mathbf{image\_capture}|\mathbf{recover}$) and status of rover hardware).
- $\mathbf{T}$, time remaining on a time-bound mission.
- $\mathbf{U(t)}$, unexplored area at time $\mathbf{t}$
- $\mathbf{ROI(t)}$, list of ROIs at time $\mathbf{t}$. Each element in this list is a Gaussian surface distributed over locations where a region of interest was detected by the rover.
- $\mathbf{loc(t)}$, rover location at time $\mathbf{t}$.
- $\mathbf{F_A(loc)}$, attractive force of a location $\mathbf{loc}$. This force is defined by the presence of ROIs (previously detected) in the rover's vicinity. The closer the rover is to one or more known ROIs, the greater the attractive force of the area.
- $\mathbf{F_R(loc)}$, repulsive force. This force is the opposite of $\mathbf{F_A}$. The repulsive force of a location $\mathbf{loc}$ has a negative effect over the rover's interest in exploring there. For example, the exploration frontier limit has a high repulsive force to prevent it from wandering off. Cliffs and other types of untraversable terrain also have higher values of $\mathbf{F_R}$.

The output of the above exploration function is the list of optimal target locations for the robot at different time instances, $\mathbf{T_{loc}}$, which is then executed by the Navigation Layer.

$$\begin{aligned} T_{loci} &= \{T_{loc1i}, ...T_{locki}\} \\ &= f(rover\_status_i, loc_i(t), T, U(t), ROI(t), F_A(loc), F_R(loc)) \end{aligned}$$

Whenever a software failure or a hardware fault is diagnosed, the rover enters the Recover mode. For instance, interference of dust storms with radio signals, power issues and sensor malfunctions, terrain obstacles and rover isolation due to geological constraints are some potential causes of temporary or extended communication loss. In such situations, the rover could, for instance, initiate the corresponding behavior sequence to reunite with its peers using visual search and predefined acoustic and visual signals (e.g., LED signals), while gathering available information from its current surroundings. Such a behavior, that is triggered in the event of loss or change in the status of communication with other team members, portrays communication-aware exploration. A reactive feedback loop will enhance system resilience, particularly whenever there is a change in communication status, triggering replanning and/or recovery (communication-aware exploration). The cost function for decision-making is thereby updated periodically based on intermediate results from exploration and recovery, and the prediction function is improved. Therefore, the proposed model is a reactive multi-layer architecture for planetary exploration by a hybrid team.

B. *Semantic Communication*

Whenever information between the rovers and the human is exchanged, messages need to be communicated over the air. To tackle the challenges of low data rate, power and latency of the hazardous environment, we break with the existing classic design paradigms of digital error-free transmission by including semantics in the wireless communications design.

Let us imagine the example in Sec. II-B of the biologist and the child to explain the idea of semantic communication: The biologist, equipped with an image sensor, captures data about a tree's botanical features such as leaves, bark, and overall structure. He wants to know what tree it is and its health status, describing his own model of the world. Instead of the raw data or message, he is interested in the meaning. Thus, it would be sufficient to communicate the semantics such as features or the final tree class or health assessment to him. Note that the inherent meaning of the identical sensed data (message) may vary when received by different entities, such as humans or specific tasks/applications, depending on the context. Envision, for instance, a child — an individual characterized by distinct attributes (personality, expertise, knowledge, goals, and intentions) compared to the biologist. This child might be solely concerned whether it can climb on a tree or whether it provides shade—a different model of the world. In both examples, we aim to discard the irrelevant information in the messages to save bandwidth, power and latency.

In this work, we adapt the idea of SINFONY— a Machine Learning—based semantic communication design approach

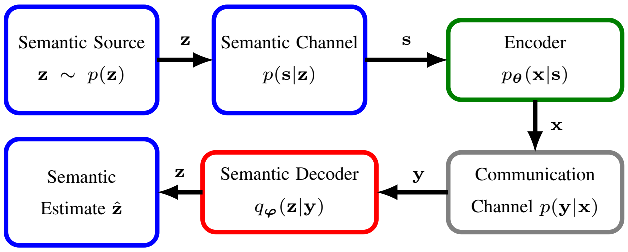

Fig. 4. Communications block diagram of the considered semantic system model from [2]. The semantic source RV $\mathbf{z}$ reflects the meaning of the classic source $\mathbf{s}$ being encoded into the transmit signal $\mathbf{x}$. After transmission over the communication channel, based on the received signal $\mathbf{y}$, the decoder estimates the semantic information.

—for integration with MAS and HMI to transmit the meaning of a message for exploration rather than its exact version [2].

1) SINFONY Approach: In [2], we define semantic communication as the data-reduced, reliable transmission of semantic sources that represent the model of the world, e.g., of biologist and child. We describe the latter as hidden target multivariate Random Variables (RV) $\mathbf{z} \in \mathcal{M}_z^{N_z \times 1}$ from a domain $\mathcal{M}_z$ of dimension N_z distributed according to a probability density or mass function (pdf/pmf) $p(\mathbf{z})$ [2]. Without loss of generality, we will assume all RVs or sets $\mathcal{M}$ either to be discrete or continuous [2]. The semantic RV reflects the task/recipient-relevant meaning of the classic source $\mathbf{s} \in \mathcal{M}_s^{N_s \times 1}$ that usually enters the communication system, as shown in the typical communications block diagram of Fig. 4. This message $\mathbf{s}$, e.g., an image or sensor signal, is entailed with the semantic RV $\mathbf{z}$ through the semantic channel $p(\mathbf{s}|\mathbf{z})$.

Then, the source $\mathbf{s}$ at the transmitter side is encoded by an encoder $p_{\boldsymbol{\theta}}(\mathbf{x}|\mathbf{s})$ with parameters $\boldsymbol{\theta} \in \mathbb{R}^{N_{\boldsymbol{\theta}} \times 1}$ into a transmit signal $\mathbf{x} \in \mathcal{M}_x^{N_{\text{Tx}} \times 1}$ for transmission over the wireless communication channel $p(\mathbf{y}|\mathbf{x})$. Based on the received signal $\mathbf{y} \in \mathcal{M}_y^{N_{\text{Rx}} \times 1}$, the semantic decoder $q_{\boldsymbol{\varphi}}(\mathbf{z}|\mathbf{y})$ with parameters $\boldsymbol{\varphi} \in \mathbb{R}^{N_{\boldsymbol{\varphi}} \times 1}$ extracts the original meaning, i.e., the semantic source in contrast to classic systems that focus on reconstructing the source $\mathbf{s}$.

In [2], we formulate the design of the communication system, encompassing the encoder $p_{\boldsymbol{\theta}}(\mathbf{x}|\mathbf{s})$ and decoder $q_{\boldsymbol{\varphi}}(\mathbf{z}|\mathbf{y})$, as an optimization problem within the framework of Information Bottleneck (IB). Our objective is to maximize the relevant mutual information $I_{\boldsymbol{\theta}}(\mathbf{z};\mathbf{y}) = \mathrm{E}_{\mathbf{z},\mathbf{y}\sim p_{\boldsymbol{\theta}}(\mathbf{z},\mathbf{y})}\left[\ln \frac{p_{\boldsymbol{\theta}}(\mathbf{z},\mathbf{y})}{p(\mathbf{z})p_{\boldsymbol{\theta}}(\mathbf{y})}\right]$ while adhering to the constraint of limiting the compression rate $I_{\boldsymbol{\theta}}(\mathbf{s};\mathbf{y})$ to a maximum information rate I_{C}:

$$\underset{p_{\boldsymbol{\theta}}(\mathbf{x}|\mathbf{s})}{\arg\max}\ I_{\boldsymbol{\theta}}(\mathbf{z};\mathbf{y}) \quad \text{s.t.} \quad I_{\boldsymbol{\theta}}(\mathbf{s};\mathbf{y}) \leq I_{\text{C}}\,. \tag{1}$$

There, $\mathrm{E}_{\mathbf{x}\sim p(\mathbf{x})}[f(\mathbf{x})]$ denotes the expected value of $f(\mathbf{x})$ with respect to both discrete or continuous RVs $\mathbf{x}$. Lower-bounding the InfoMax term in the IB problem (1) by the negative amortized cross-entropy $\mathcal{L}_{\boldsymbol{\theta},\boldsymbol{\varphi}}^{\text{CE}}$ and fixing the transmit dimension to N_{Tx}, we can optimize encoder and decoder parameters [2]:

$$\mathcal{L}_{\boldsymbol{\theta},\boldsymbol{\varphi}}^{\text{CE}} = \mathrm{E}_{\mathbf{s},\mathbf{x},\mathbf{y},\mathbf{z}\sim p_{\boldsymbol{\theta}}(\mathbf{s},\mathbf{x},\mathbf{y},\mathbf{z})}[-\ln q_{\boldsymbol{\varphi}}(\mathbf{z}|\mathbf{y})] \tag{2}$$

$$\{\boldsymbol{\theta}^*, \boldsymbol{\varphi}^*\} = \underset{\boldsymbol{\theta},\boldsymbol{\varphi}}{\arg\min}\ \mathcal{L}_{\boldsymbol{\theta},\boldsymbol{\varphi}}^{\text{CE}}\,. \tag{3}$$

To solve (3), we use ML-techniques such as Stochastic Gradient Descent and the reparametrization trick. We design encoder and decoder with DNNs and apply model-knowledge in the selection of the layers, e.g., process images with ResNet layers. By this means, we obtain our ML-based design Semantic INFOrmation TraNsmission and RecoverY (SINFONY) [2]. In [39], we extend the approach by Reinforcement Learning (RL) into RL-SINFONY such that it can be optimized with separated transmitter and receiver as well as without a known or differentiable channel model—a crucial step towards deployment in practice.

Finally, we apply our ML-based design SINFONY to a distributed multipoint scenario, communicating meaning from multiple image sources, e.g., rover sensors, to a single receiver for recovery of semantic information, i.e., of the image classes or content. In the numerical example of [2], four distributed agents extract features with an encoder based on the ResNet architecture for rate-efficient transmission. Based on the received signals, the decoder extracts semantics by classification. The results from numerical experiments using images from the MNIST and CIFAR10 dataset, as presented in [2], indicate that SINFONY can operate effectively at a rate-normalized SNR up to 20 dB lower than classical digital communication systems.

2) Integration of SINFONY: We leverage SINFONY for seamless integration with MAS and HMI due to its remarkable adaptability to diverse use cases, including resource localization. This adaptability is achieved through the modification of data samples and the customization of both the encoder and decoder DNN architecture. Further, we need to define the format of the semantic RV: We plan to extract semantic information from the rover image sensors, such as type of resources and position of the resources. Then, we forward this probabilistic output $q_{\boldsymbol{\varphi}}(\mathbf{z}|\mathbf{y})$ or hard output $\mathbf{z}$ of the semantic decoder to the HMI. There, we visualize this output such that the meaning of the data becomes clear to the human operator.

C. Visualization and simulation environment

The challenge for the visualization and simulation of the human-machine interaction is to provide both the human explorer and operator with the relevant input for decision-making. In both cases, a human-in-the loop approach is implemented for the simulation.

The human explorer actively engages in the simulation, primarily within a VR environment. This immersive setup aims to provide the explorer with a comprehensive and immersive experience to visually explore the terrain of Mars. By being immersed in this VR environment, the explorer gains a firsthand, immersive understanding of the visual data gathered by the rovers or exploration devices. The explorer's role involves experiencing and interpreting visual impressions from the simulated Martian environment. This perception allows for a deeper understanding of the terrain, potential obstacles, or interesting features that might be encountered during exploration missions. Additionally, the human explorer might serve as a communication relay during larger missions. This involvement in relaying information could be crucial for ensuring seamless and efficient communication between different mission elements, enhancing overall coordination and information flow.

The human operator receives real-time data streams from a software-in-the-loop simulation of the rovers or other exploration devices. This data provides critical information about the ongoing operations, including sensor readings, environmental conditions, or equipment status. Alongside real-time data, the operator also receives visual render streams from the VR environment where the human explorer is immersed. These render streams aim to provide the operator with a visual representation of what the explorer is experiencing, facilitating informed decision-making regarding mission directives, navigation, or potential course corrections. The operator's role involves overseeing the simulation and making real-time decisions based on the interpretation of received data and visual representations. This might include directing the exploration devices, adjusting mission parameters, or responding to unforeseen challenges.

A central aspect to the visualization is the semantic communication. Not all data is transmitted, only the information relevant to each respective decision. The following examples include the usage of semantic information. In each of these cases, the idea is to communicate only the essential information needed for effective decision-making, streamlining the communication process and optimizing human-robot interaction.

1) Rover Navigation: Instead of sending every sensor reading to the operator, the rover selectively transmits obstacle detection data or changes in terrain topology that could impact its path. This allows the operator to make informed decisions about rerouting without overwhelming them with unnecessary details.
2) Task Allocation: When reporting finished tasks to the human operator or explorer, the rover communicates only the pertinent details about the location of markers (ROIs) or anomalies, enabling the human to focus on those specific objectives rather than inundating them with extraneous data.
3) Resource Management: In a scenario where energy levels are critical, the rover transmits only crucial battery status updates or power consumption trends, aiding the operator in making decisions about conserving energy or altering exploration priorities.
4) Environmental Analysis: The rover selectively sends specific environmental data (like temperature fluctuations or air quality metrics) relevant to potential hazards, allowing the operator to assess risks without overwhelming them with comprehensive but less pertinent sensor readings.
5) Adaptive Decision-Making: During unpredictable scenarios, the rover might transmit real-time information about sudden changes in the terrain or unexpected obstacles, enabling swift adjustments in exploration strategies without flooding the operator with continuous updates.

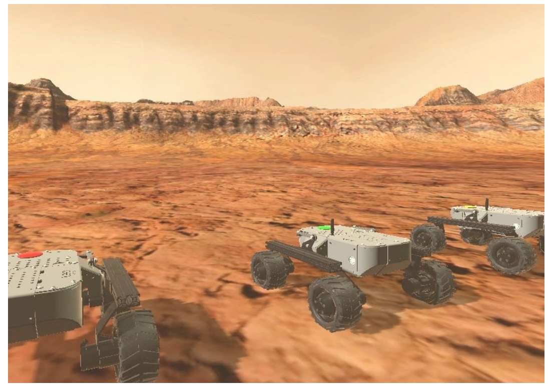

Fig. 5. XR scenario with three rovers.

IV. Implementation

We first implement and test the framework in a simulated environment. The scenario is simulated using a simulation software called Machina Arte Robotum Simulans [40]. RoCK acts as a framework for operating the robots. In order to include the human explorer, we implement a Human-in-the-Loop simulation based on the game engine Unity 3D. The human explorer can experience the simulation environment by wearing a head-mounted display and interacting with the rover team (task allocation) as shown in Fig. 5 by using gaming controllers. The human-rover interface is implemented by using an Ethernet socket connection, allowing a Hardware-in-the-Loop simulation of the rovers. The first use case is based on an exploration scenario, including three Leo Rovers 1.8 from fictionlab and a human explorer. A human operator can access the simulation by connecting to a render stream from the Unity engine. Both, the Human-in-the-Loop and Hardware-in-the-Loop simulation data can be accessed that way.

The rovers and the human explorer can search for the randomly distributed markers (ROIs) individually. Either the human operator or explorer can confirm the detection of an ROI depending on the available data. We implemented the semantic communication system SINFONY in TensorFlow 2. The source code is available in [41]. For practical implementation, we plan to use software defined radios.

V. Conclusion and Outlook

In this work, we proposed a conceptual framework for human-integrated swarm exploration. To achieve this, we created a mathematical framework for semantic communication [2] with the implementation SINFONY. In order to numerically evaluate the applicability of the framework, we will first conduct simulation trials with a human-in-the-loop approach to assess the performance of the robotic exploration algorithm in various planetary exploration scenarios. The evaluation will be based on metrics like total exploration time, exploration efficiency (RoIs found, redundancy, energy conserved), and ease of interpretation of semantic information by the test subjects. The last will also be verified in retrospect via a questionnaire. The trials will include a human operator (test subject), human explorer (simulation) and a robotic swarm (simulation).

Finally, we plan a hardware-integrated demonstration with explorers and robots, enabling a real-world experience to verify the results from simulation trials. This experiment aims to examine the interaction dynamics between operator, explorer and the swarm concerning decision-making during exploration missions under sparse communication and challenging environmental conditions.

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