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Invited Paper

Intelligent Systems for the Autonomous Exploration of Titan and Enceladus

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ABSTRACT

Future planetary exploration of the outer satellites of the Solar System will require higher levels of onboard automation, including autonomous determination of sites where the probability of significant scientific findings is highest. Generally, the level of needed automation is heavily influenced by the distance between Earth and the robotic explorer(s) (e.g. spacecraft(s), rover(s), and balloon(s)). Therefore, planning missions to the outer satellites mandates the analysis, design and integration within the mission architecture of semi- and/or completely autonomous intelligence systems. Such systems should (1) include software packages that enable fully automated and comprehensive identification, characterization, and quantification of feature information within an operational region with subsequent target prioritization and selection for close-up reexamination; and (2) integrate existing information with acquired, "in transit" spatial and temporal sensor data to automatically perform intelligent planetary reconnaissance, which includes identification of sites with the highest potential to yield significant geological and astrobiological information. In this paper we review and compare some of the available Artificial Intelligence (AI) schemes and their adaptation to the problem of designing expert systems for onboard-based, autonomous science to be performed in the course of outer satellites exploration. More specifically, the fuzzy-logic framework proposed is analyzed in some details to show the effectiveness of such a scheme when applied to the problem of designing expert systems capable of identifying and further exploring regions on Titan and/or Enceladus that have the highest potential to yield evidence for past or present life. Based on available information (e.g., Cassini data), the current knowledge and understanding of Titan and Enceladus environments is evaluated to define a path for the design of a fuzzy-based system capable of reasoning over collected data and capable of providing the inference required to autonomously optimize future outer satellites explorations.

Keywords: Fuzzy expert systems, autonomy, planetary reconnaissance, exploration of the Solar System, Titan, Enceladus.[1]

1. INTRODUCTION

Autonomy will play a critical role in future science-driven and less constrained exploration of extremely challenging planetary environments characterizing the outer portion of the Solar System (e.g., Titan, Enceladus, Europa). Such planetary bodies have a high potential of yielding significant geological and possibly astrobiological information, and lately received a great deal of attention from NASA, ESA, and other space agencies. Indeed, the Outer Planet Assessment Group (OPAG) [1], established by NASA in 2004, identified scientific priorities and pathways for exploration in the outer Solar System. This group advocates large-effort flagship missions, designed to optimize the overall science return and to increase the

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understanding of the outer solar planets. The full-scale and optimal deployment of agents (e.g., orbiter(s), balloon(s), lander(s)), employed by any flagship mission [2] or tier-scalable reconnaissance mission [3], requires the design, implementation, and integration of an intelligent reconnaissance system [4-6]. Such a system should be designed to enable fully automated and comprehensive characterization of an operational area, as well as to integrate existing information with acquired, "in transit" spatial and temporal sensor data, to identify and home in on prime candidate locales, including locales with the greatest potential of containing life.

To address such open questions, our team has been working on a systematic set of fuzzy-based expert systems capable of evaluating the geologic and astrobiological information acquired during the course of automated outer Solar System reconnaissance missions. We believe that such systems are a straightforward and effective way to execute artificial reasoning for autonomous and intelligent real-time science. Here, we review the idea of using fuzzy logic for planetary exploration [5, 6] and we adapt the design and implementation of fuzzy expert systems for autonomous reconnaissance to the case of Titan as it is one of the targeted candidates for the next flagship mission. After comparing and contrasting various possible artificial intelligent schemes, a case for using fuzzy logic in such specific application is made. Subsequently, the problem of using fuzzy expert systems for the exploration of Titan and Enceladus is discussed. It will be shown that such systems are not only an attractive way of doing planetary exploration but may be critical to execute successful reconnaissance of environments where communication delays virtually forbid human-based real-time reaction, commanding and guided execution. Indeed, the idea of exploring Titan using long-duration hot-air balloon platform would be seriously hampered if a proper guidance, navigation and control (GNC) system were not implemented on-board for autonomous navigation [7]. Such a system may be conceived to host one or more fuzzy experts for real-time, in-transit autonomous interpretation of scientific data to assess the locales with the highest potential for scientific findings. Focusing on the exploration of Titan, the fuzzy system architecture, implemented and run on a hot-air balloon microprocessor, is analyzed. Subsequently, a detailed explanation of how to construct the appropriate knowledge-base for Titan habitability assessment is presented to highlight the overall potential of this methodology.

2. FUZZY PARADIGM APPLIED TO PLANETARY EXPLORATION

2.1 Why fuzzy logic?

Planetary exploration is about understanding the history of celestial bodies through remote and/or in-situ data collection. In such an endeavor, novel discoveries are made using newly acquired data, which permit the testing of working hypotheses and/or formulation of new hypotheses. The fuzzy logic semantic provides an ideal framework to deal with multiple layers of information of varying degrees of confidence such as elevated methane content, low sulfate level, and medium number of valley networks. The absolute values of the input data can be transformed into fuzzy values and incorporated into rules that deal with concepts/working hypotheses of varying degrees of confidence. Thus, fuzzy logic provides a powerful framework that can be exploited to design expert systems to be embedded in any kind of reconnaissance mission architecture for planetary exploration.

2.2 Fuzzy logic versus other Artificial intelligence schemes

Designing expert systems to autonomously assess the potential exhibited by the observed area during the course of planetary reconnaissance is a knowledge engineering problem. In its basic formulation it can be stated as follows: given the domain-containing input data, find a suitable solution among all possible candidates occurring in the solution space. Interpreted in the sense of the problem that we are tackling, input data refers to both information collected via multi-sensor platform deployment and existing (published information). On the other hand, a solution must be interpreted as the answer to one of the questions we are posing, while investigating planetary bodies. For example what is the potential that the area under observation yields significant scientific findings (e.g., harbor life). If the quest is to provide answers in real-time (i.e., while exploring) and in an automatic fashion, field-based knowledge must be implemented on a computer. Knowledge can be defined as "condensed information" and as far as we are concerned, it consists of rules or methods from which it is possible to perform plausible reasoning to obtain new facts and hypotheses. To autonomously evaluate and infer new facts from data, knowledge must be coupled with inference schemes. For our purpose, inference is defined as the process of matching data and knowledge to infer new. Knowledge is usually acquired and integrated via the inference mechanism.

Independent from the method of choice employed to define an expert for autonomous exploration of planetary bodies in the Solar System, any Artificial Intelligence (AI) scheme must be able to deal with the major knowledge engineering issues of how to adequately represent knowledge and inference. More specifically, representation, inference, learning, generalization, explanation and adaptation capabilities must be carefully analyzed and properly selected to provide a satisfactory solution to the posed problems. Various schemes are possible. For example, symbolic AI, Fuzzy logic-based and neural networks schemes provide different frameworks that can generate intelligent schemes suitable for effective autonomous, science-driven planetary reconnaissance. The differences between the mentioned algorithms can be briefly highlighted. Neural networks fall under the category of connectionist systems. In such cases, knowledge is distributed among various nodes. Indeed, neural networks are constructed in such a way that knowledge is unstructured as they learn by examples, by doing or by analogy. Moreover, they are capable of good generalization and adaptation. Conversely, symbolic AI and fuzzy systems are conceived and designed to represent structured knowledge. While inference is exact in symbolic AI, it is approximate in fuzzy-based and neural network systems. Symbolic AI systems do not deal very well with missing, corrupted and inexact data.

When dealing with the problem of defining AI schemes for planetary reconnaissance and exploration, how to represent uncertain knowledge and uncertain data is another critical issue that must be addressed. While fuzzy methods are inherently capable of dealing with uncertainties, probabilistic methods may represent an attractive alternative. If one relies on the axioms of probability as a mathematical framework, coherent knowledge-bases can be built using a) data collected in the course of past missions, b) statistical methods to determine the appropriate conditional probabilities (objective probability), and c) conditional probabilities that define beliefs unsupported by data (subjective probability). In a nutshell, probabilistic methods are based on estimating the posterior probability for a conclusion (defined by a rule) to be accepted as correct. The major drawback of probabilistic approaches stem from the fact that such methods cannot deal with ambiguous and contradictory scenarios. Generally, Bayes' theorem fails whenever multiple rules reach different conclusions if a condition is true. Conversely, fuzzy systems can deal with contradictory and ambiguous rules by naturally providing a trade-off during the inference process (rules are fired at the same time).

At the current time, we believe that fuzzy-based systems represent an ideal solution for autonomous science-driven, less constrained planetary reconnaissance. As explained in the course of our discussion, structured knowledge is directly implemented by intuitive, easy-to-devise, fuzzy rules that can facilitate the interaction between planetary scientists and computing devices. It is important to remember that, fuzzy logic shares the same basis of human communication and therefore, while dealing with the unknown and uncertainty found during the course of planetary exploration, fuzzy systems will be able not only to make autonomous decisions but also to provide good and solid explanations facilitating the human-machine interaction. In our interpretation, planetary experts, such as geologists and astrobiologists, will be required to provide their knowledge to effectively contribute both to the design and testing phase while working on finding a common ground with computer and AI engineers.

3. FUZZY EXPERT SYSTEMS FOR THE EXPLORATION OF TITAN AND ENCELADUS

While making the case for fuzzy expert systems as a premiere choice for autonomous decision-making and data interpretation, we need to explore how such systems can be adapted to exploration scenarios that involve the outer portion of the Solar System, including Titan and Enceladus. It is legitimate to pose the following question: how does the effectiveness of fuzzy systems for planetary reconnaissance vary as a function of the observed planetary body? Two major factors must be considered, i.e., 1) the ability of the system to acquire and store data and 2) the distance of the explored planetary body from Earth. For any mission architecture, the level of required autonomy increases (non-linearly) with the distance between the deployed observing platform(s) and Earth. Consider Titan and Enceladus as explored by the Cassini orbiter: A great deal of information is continuously streamed back to Earth unveiling novel features of these two Saturnian satellites, which are a minimum of 2.2 hours round-trip light-time from our planet. For example, Cassini radar observations and the Huygens descent/landing probe unveiled apparent methane lakes, riverbeds, coastlines [8], and dunes [9] on Titan. Enceladus' geological activity is under scrutiny as well: closer observations of the Saturnian satellite, as imaged by Cassini, revealed an interesting world where tectonic activity and cryo-volcanism dominated the satellite geologic history and where geyser-like eruptions continued in real-time during Cassini's exploration [10-12].

In relation to its ability to acquire and retain data, it is important to recall that Cassini is equipped with 12 instruments for remote data collection and most of its operations are constrained by instrument resolution and atmospheric effects [13]. Science data are stored in the Solid-State Recorder (SSR), which has the ability to retain 2 Gigabits of data. Clearly, data storage becomes a factor since if the collected bits exceed the storage capability, information must be erased. Blind (non-intelligent) acquisition of all observed data might be improved by an on-board autonomous system that can acquire data that contain high scientific value. As far as distance is concerned, since the spacecraft is located between 8.2 and 10.2 Astronomical Units (AU) from Earth, it takes about 68 to 84 minutes to communicate/relay information back to ground stations. Real-time communication is impossible and as a matter of fact, it takes a minimum of 3 hours for the system (including human beings) to react to any on-board problem. Software can diagnose problems only to a limited degree, but if the problem appears to be too severe, the spacecraft is put into a safe mode and is essentially shut down until humans can diagnose and fix the problem. A similar approach to fault tolerance caused the Galileo spacecraft at Jupiter to lose close to half its data collected at the most interesting close approach phases. Such 'safe mode' events have been far fewer but have impacted the Cassini mission as well. The absence of robust software capable of autonomous decision making and control jeopardizes the ability of the system to perform optimal reconnaissance.

The discovery of critical phenomena occurring during the course of planetary reconnaissance is much more problematic and is the major theme of this work. These phenomena are uncertain, poorly understood and may be transient or at best observable for shot periods of time.

The recognition, detection and categorization of interesting transient and static phenomena observed during the course of planetary reconnaissance happen according to the following sequence: (1) autonomous recognition of what may constitute an important discovery; (2) autonomous prioritization of the discovery relative to other observation and engineering maintenance tasks; and (3) the autonomous development of an observation strategy if the phenomenon should be deemed to be important enough to formulate and insert new observations. Current state-of-the-art systems are unable to autonomously make such decisions and implement the required action and therefore many phenomena may remain undiscovered or, if discovered, may not be followed up. This is a severe handicap especially when dealing with phenomena that may be difficult to detect due to their transient nature, due to low frequency or low concentration relative to detection thresholds, or due to observability only from special vantages. The capture of a discovery is especially challenging when the phenomenology is not yet known, and therefore it is not predictable by traditional means of spacecraft observation. The consequence is that some of the things we most search for in the Solar System may be essentially impossible to find with current mission and observation approaches.

While we believe that a hot-air balloon deployed in the Titan environment will be central to the next flagship mission to the Saturnian satellite, any system equipped with fuzzy-based experts may effectively overcome the limitation imposed by Earth communication delays and data storage as well as address the problem of real-time capture of new transient phenomena. Despite the fact that the overall amount of data collected during the course of a long-term balloon mission could be extremely large, a suite of fuzzy-based expert systems for scientific assessment and global/regional/local interpretation can effectively retain only data that yields significant findings; thus, the integrated system can concentrate its actions on locales worth of exploration using the platforms and sensors best suited to make the observations (see also [14]).

Importantly, such expanded platform/sensor systems may also work in a semi-autonomous mode. For example, on Titan, the system might select potentially interesting, information-rich sites concentrated around zones of mobile condensed hydrocarbons (e.g., lakes), send the acquired information back to Earth and initiate a human-machine interaction where the humans analyze both system results and explanations.

As a result, humans could command further investigation or alternatively disregard the selected areas. At Enceladus, following a similar pattern, the system might be designed to look specifically for transient geyser eruptions and geothermal emissions and focus observations on the phenomena deemed most interesting or most suitable for safe observations.

Eventually, systems may be designed that have no particular a priori programming of what constitutes something of interest; the system will map surfaces, compositions, and energy fields, look for changes, identify anomalies, establish a physical meaning of the anomalies, prioritize the importance and significance of the phenomenology, and devise an automated approach to making further observations (see also [15, 14, 16] for a precursor of such a system). We are obviously a very long way from such human-like artificial intelligence, which would be necessary, for example, in the exploration of extrasolar planetary systems using interstellar probes. For now, we keep our focus much nearer to home and apply this methodology to a problem of paramount importance to NASA and other space agencies: the detection of extraterrestrial life or its fossils.

3.1 Fuzzy Expert System Design: Titan balloon application

While our team has been tackling a broad range of fuzzy systems [4-6] conceiving architectures for planets with very different geologic histories (e.g., Mars and Enceladus), our focus has recently shifted toward Titan. The sixth Saturnian moon is characterized by an extremely rich and complex environment. As shown in Figure 1, Cassini radar observations and the Huygens descent/landing probe unveiled apparent methane lakes, coastlines, and riverbeds [8], [17]. Due to its thick atmosphere, a flagship mission envisioning the deployment of a hot-air balloon is under investigation [2].

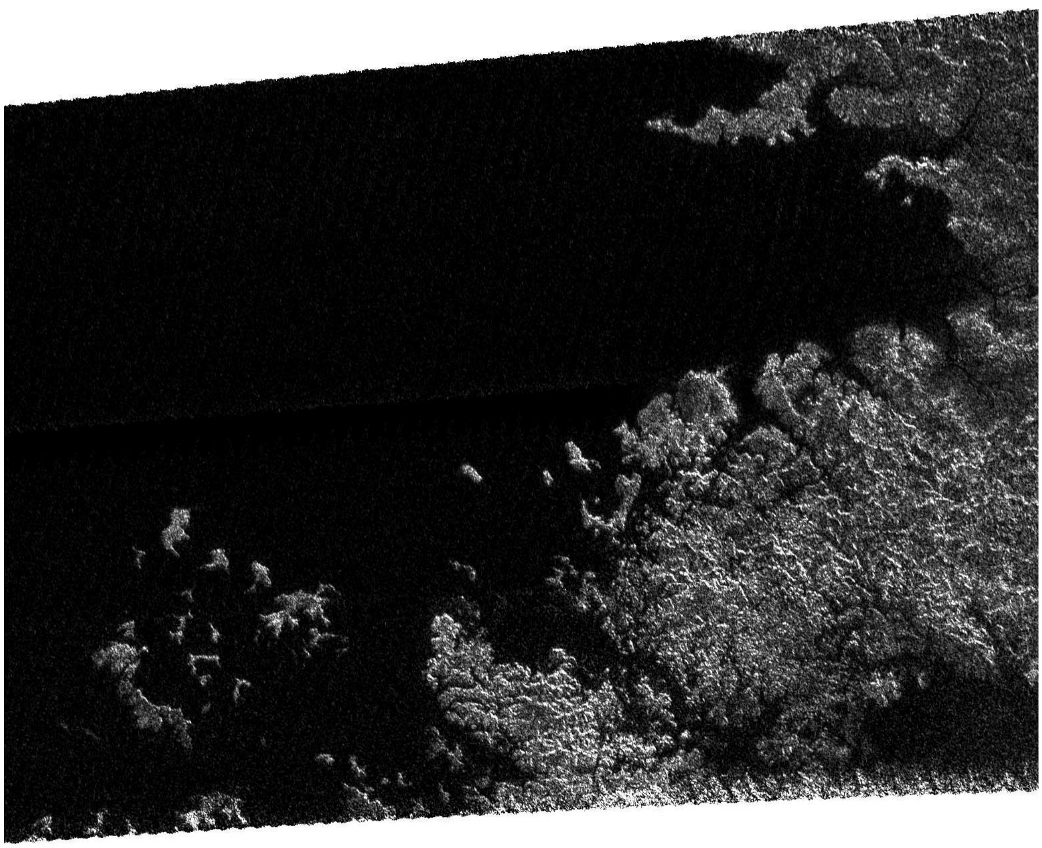

Fig. 1.Radar image obtained by Cassini's on-board radar instrument during a near-polar fly-by (May 13, 2007). As with other bodies of liquid seen on Titan by Cassini, we can see channels, islands, bays, and other forms typical of terrestrial coastlines, and the liquid, which is most likely a combination of methane and ethane, appears very dark to the radar. Photo courtesy of NASA/JPL.

As explained in the previous section, because of the far distance from Earth, real-time communication with such a balloon is impossible and therefore autonomous navigation and reasoning becomes imperative. In a highly automated scenario, the deployed hot-air balloon should be able to ingest multiple layers of information (e.g., elemental, stratigraphic, topographic, thermal, atmospheric, spectral) and autonomously assess the potential, exhibited by the locale under observation, to yield significant information. Figure 2 shows how an intelligent reconnaissance system can be integrated into a baseline balloon architecture, assumed to be deployed on Titan. Firstly, the acquired data are categorized and pre-processed via embedded software packages, such as the Automated Global Feature Analyzer (AGFA) [15, 16], to provide the numerical values for the indicators appropriate for scientific inquiries. Such indicators are then fed into the expert fuzzy system that processes the information and assesses the potential for, for example, fluvial activity, cryovolcanism, and/or local habitability. Subsequently, the fuzzy expert interacts with the lower level control system and commands the balloon to take appropriate actions such as initiating a descent for closer surface examination, station keeping, or even collecting surface samples [7]. Figure 2 also shows the elements forming the backbone of the discussed fuzzy expert system. The core of the fuzzy system, which is called knowledge base, comprises fuzzy rules and membership functions. The rules are linguistic statements condensing expertise, methods, and skills that are derived from years of investigation. For our design and simulation, we employ Mamdani-type IF-THEN rules [18]. The fuzzy inference engine defines the process of formulating the mapping given the data. Such an inference engine uses the pre-defined rules, (fuzzy) data, and observations to infer new facts. Finally, a user interface (explanation module) is required to explain why and how the solution has been reached. The module is used by humans to remotely monitor the operations of the system.

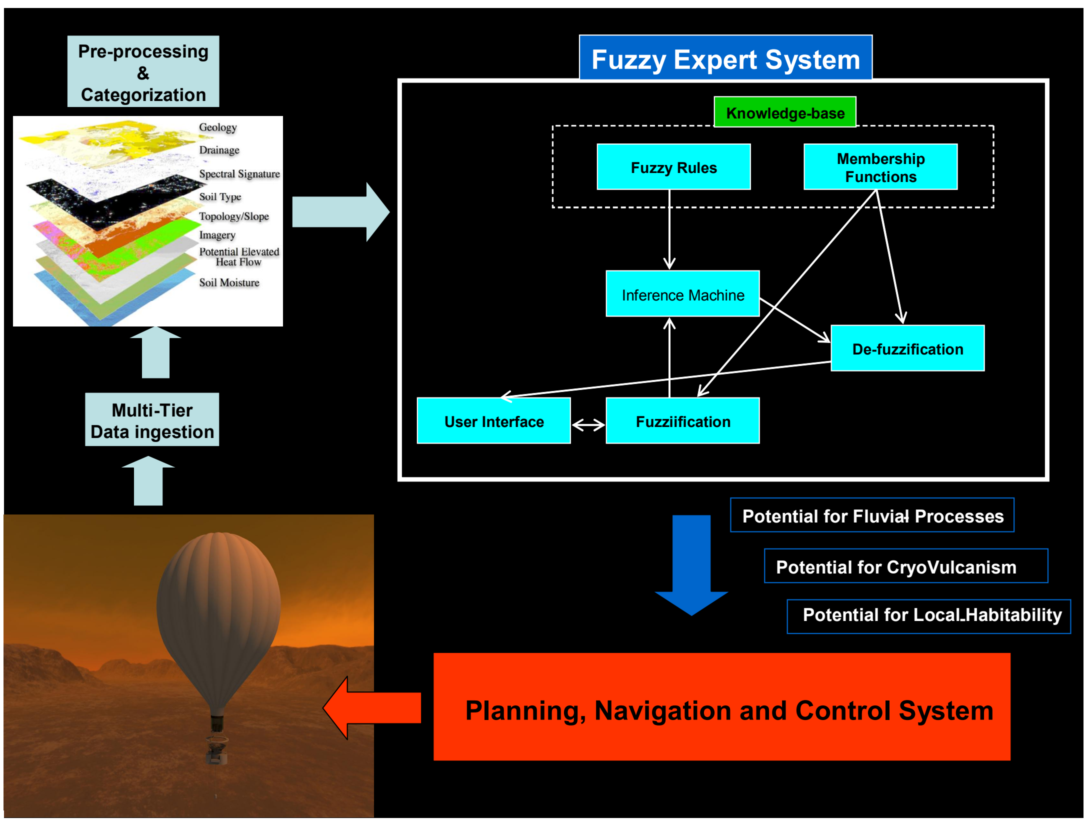

Fig. 2. Intelligent reconnaissance system embedded on a hot-air balloon deployed for the exploration of Titan. Data are acquired while in transit from the on-board instruments. After pre-processing and categorization, the appropriate indicators are fed into a fuzzy expert system to assess the potential for scientific findings. Moreover, the fuzzy expert interacts with a lower level control system to implement, based on the fuzzy assessment, the desired course of action. Balloon artistic image courtesy of Tibor Balint, NASA/JPL

3.2 Knowledge-base for the exploration of Titan: Fuzzy design for life assessment

This section is devoted to the problem of designing a fuzzy expert system for local habitability assessment that can be implemented and integrated in the hot-air balloon mission architecture for the exploration of Titan. The key to the fuzzy system design is the definition of a proper architecture centered on defining an appropriate knowledge-base that can effectively mimic the way of thinking of an astrobiologist in the quest for life while exploring the Saturnian satellite. Moreover, because of the multi-disciplinary approach required by the general problem of searching for life in the Solar System, this task also represents an attempt to merge biology with other disciplines such as geology and chemistry by establishing the proper connection between presence of life and the characteristics of a geological environment. Such connection is implemented in a knowledge-base that can be accessed by the balloon-based expert system for inference on data acquired during the course of the reconnaissance of Titan.

Generally, life requires basic ingredients, i.e., energy, chemistry, solvent, and habitability [19]. Energy is abundant throughout the overall Solar System and can take different forms such as electromagnetic, chemical, thermal, etc. Titan is located far away from the sun so that solar radiation is of lesser importance than other forms of energy such as geothermal (i.e., the ratio solar/geothermal energy is very low). Other forms of energy could be in principle effective as well (e.g., gravity, pressure). Both inorganic and organic chemical bonds may contain energy that can be harvested to sustain life. As for the importance of chemistry, it is shown that life resides in complex polymeric chemistry based on a covalently bonded carbon backbone. Carbon is shown to have impressive advantages over other compounds although silicon-based life could be conceived because silicon provides stability and lability under a fairly broad range of conditions. In addition, to be sustained, life requires the presence of a solvent, i.e., a liquid medium to sustain dynamic transactions. Water is clearly the utmost candidate although in the case of Titan, where water cannot be liquid due to its extremely low temperature conditions, liquid methane and ethane become the primary solvent candidates. Habitability plays an important role as planetary surface processes might provide an opportunity to generate sub-habitats with specific but periodically changing characteristics. As terrain and sub-terrain variation might create microenvironments favorable to life, the connection with geomorphology should be an integral part of the knowledge-base for autonomous inference of habitability assessment.

For the case of Titan, we focus on four basic ingredients to sustain life, i.e., an energy source, a set of organic molecules, the presence of a solvent and the capability of the observed system to contain molecules for energy storage. Based on such ingredients, we conceived an expert system comprised of a cascade of five (5) independent fuzzy systems arranged in a two-layer configuration. Figure 3 shows the basic architecture as embedded in the on-board hot-air balloon microprocessor. As the balloon navigates the Titan environment, data are acquired by the instrument suite and preprocessed to extract the basic life indicators. Such indicators are categorized and fed into four independent fuzzy experts, each specialized to determine the potential for energy (PE), organic molecules (POM), energy-storage molecules (PES) and solvent (PS) exhibited by the observed area. Such independently evaluated indicators are then fed into a second layer comprised of one fuzzy expert that, equipped with an appropriate knowledge-base, is capable of reasoning over the data to infer the life potential (LP) exhibited by the observed region.

The knowledge-base of each of the five fuzzy systems forming the backbone of the expert architecture is comprised of IF-THEN rules (i.e., Mamdani-type) that can implement appropriate knowledge in a language understandable by a digital computer.

Firstly, for each of the expert systems, the indicators must be established. Consider for example the first-layer fuzzy expert system designed to determine the potential for energy (PE). Two indicators that are direct evidence of thermal energy are temperature and heat flux. Subsequently, one should consider parameters that are connected to geothermal and/or volcanic activity such as presence of calderas, high volatiles in the atmosphere (such as methane and ethane), low temperature cryolavas (ethaline), and high temperature cryolavas (water ammonia). Moreover, the analysis of surface geomorphology might indicate tectonic activity, e.g., detection of faults, joints, and basins. The fuzzy expert designed to evaluate the potential for organic molecules (POM) should heavily rely on hyperspectral data to identify the absorption bands of the major organic components. A comprehensive spectrum of organic components likely to be found on Titan and their impact to presence of life (through a confidence factor that weights the relative importance with respect to each other) should be listed as POM indicators. A similar reasoning applies to the identification of compounds capable of storing energy available to sustain life (similar to the Earth-based phosphates) that should be listed as indicators for the fuzzy system determining the PES. The system designed to acquire the indicators appropriate for determining the PS parameter requires a closer examination. On Titan, the premiere solvent candidate is methane. Clearly, direct identification of methane is of first order importance. Nevertheless, liquid methane may be responsible for a large spectrum of surface (fluvial) processes shaping Titan's body. Therefore, geomorphological indicators play an important role as indirect evidence of liquid bodies (as connected to methane and any other solvent). Indeed, alluvial fans, valley networks, basins, streamlined bedforms, anastomosing patterns, should all be included as solvent indicators.

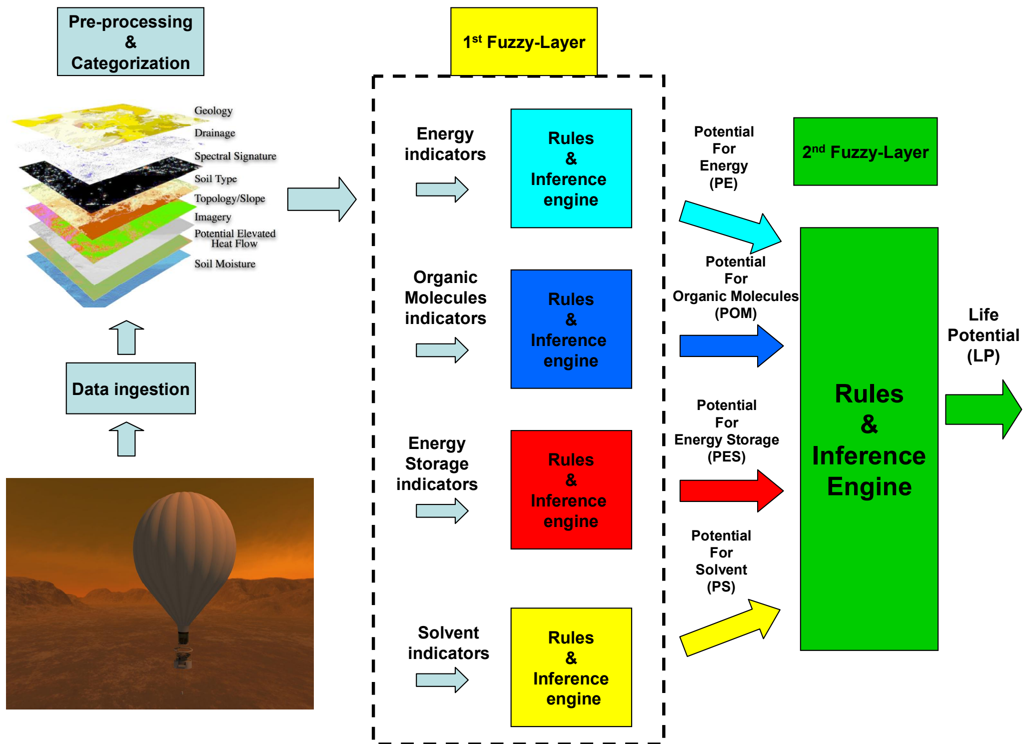

Fig. 3. Two-layer fuzzy system architecture for life potential assessment. The system is comprised of 5 independent fuzzy systems organized in two interconnected layers. Balloon artistic image courtesy of Tibor Balint,

a

b

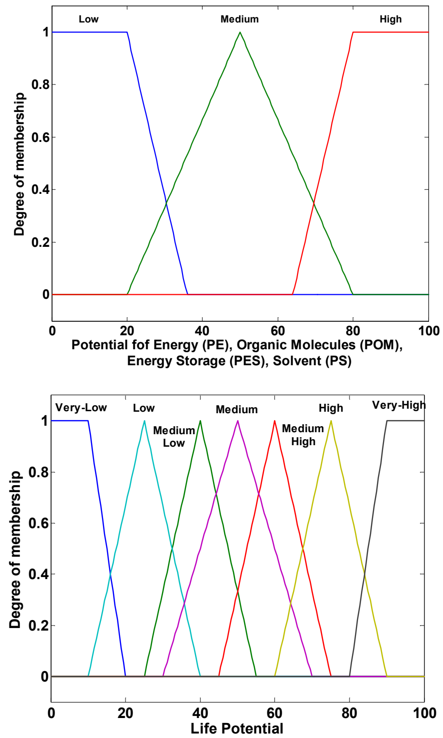

Fig. 4. Membership functions for the inputs (PE, POM, PES and PS) and output (LP) of the second-layer fuzzy expert system. The functions represent the notional concepts of "high", "medium", "low", etc.

To illustrate how the knowledge-base is designed and implemented, we focus our attention on the second layer of the proposed fuzzy architecture. As explained above, the second layer is fed by the output of the first layer. In essence, the four independent first-layer fuzzy systems forward the evaluated PE, POM, PES, and PS to the second-layer fuzzy expert that elaborates upon such indicators to evaluate the LP parameter, which is the output of the overall fuzzy expert system. Table 1 shows the complete set of rules. The input values are linguistically described as high (H), medium (M), and low (L). Their membership functions are reported in Figure 4a. The LP parameter (varying between 0 and 100) is linguistically described by seven membership functions (reported in Figure 4b), i.e., very high (VH), high (H), medium-high (MH), medium (M), medium-low (ML), low (L), and very low (VL). We constructed a knowledge-base comprised of 71 rules, which are fired concurrently to reason upon the indicator values. The overall idea is that the life potential obtains the highest value if the life indicators are such that the potential for energy, organic molecules, energy storage and solvent are all high. Indeed, rule #1 of Table 1 is a short visual representation for the following rule:

IF PE is H AND POM is H AND PES is H AND PS is H THEN LP is VH

All rules follow a similar pattern and explore all possibilities in relationship to every combination of life indicators.

Implementation, simulation and analysis of the system performance require the usage of dedicated software (e.g., MATLAB fuzzy logic toolbox) for rapid design development. Full-scale implementation and testing is underway and will be reported in the near future.

4. CONCLUSIONS AND FUTURE EFFORTS

In this paper we presented how the fuzzy logic framework can be adapted to design and implement fuzzy expert systems for autonomous exploration of the outer planets of the Solar System and more specifically for the exploration of Titan and Enceladus. We analyzed the problem from a fundamental point of view, comparing a variety of AI schemes, including neural networks, symbolic AI and probabilistic methods and we made a case for using fuzzy logic as a preferred choice. It is shown that for future flagship missions, either to Titan or Enceladus (as well as Europa), autonomous intelligent systems capable of reasoning over the stream of acquired data are critical to increase the level of scientific return. Fuzzy expert systems can be designed to assess the potential of the observed area to yield scientific findings including life. Such systems are extremely effective in acquiring geomorphological, topographical, spectral, elemental, and thermal information, to autonomously decide if the observed area should be granted a closer examination. Such decision capabilities can be coupled with the Guidance, Navigation and Control (GNC) system architecture of the deployed reconnaissance platform to provide commands to the platform to home in on the observed locale. The latter depends on the homing capability of the reconnaissance system. As an example, we considered the problem of designing the architecture of a fuzzy expert system to be implemented on the microprocessor guiding the motion of a hot-air balloon deployed as a long-duration platform for the exploration of Titan. More specifically, we outlined the architecture of a two-layer fuzzy expert comprised of five interconnected, independent fuzzy experts capable of assessing the life potential from appropriate life indicators (energy, organic molecules, energy storage and solvent). As shown in the previous section, the critical component that must be defined, implemented and analyzed is the appropriate knowledge-base for efficient reasoning over the acquired data. Future efforts will include full-scale implementation, simulation and testing of the system using real Titan observational data (i.e., Cassini-data). Importantly, the approach is shown to be modular and has the potential to be tailored to the exploration of any planetary body of the Solar System.

Table 1. Rule-table for the knowledge-base of the second-layer fuzzy expert. The table shows rule number, indicator's input value expressed in linguistic fashion (high, medium, low), logical connector (e.g., AND, OR) and life potential linguistic expression (very high, high, medium-high, medium, medium-low, low, very low).

Rule	PE	POM	PES	PS	Conn	LP	Rule	PE	POM	PES	PS	Conn	LP
1	H	H	H	H	AND	VH	37	M	H	L	M	AND	M
2	H	H	H	M	AND	H	38	M	H	L	L	AND	ML
3	H	H	H	L	AND	MH	39	L	H	M	M	AND	M
4	H	H	M	H	AND	H	40	L	H	M	L	AND	ML
5	H	H	L	H	AND	MH	41	L	H	L	M	AND	ML
6	H	M	H	H	AND	H	42	L	H	L	L	AND	L
7	H	L	H	H	AND	MH	43	M	M	H	M	AND	M
8	M	H	H	H	AND	H	44	M	L	H	M	AND	M
9	L	H	H	H	AND	MH	45	L	M	H	M	AND	M
10	H	H	M	M	AND	MH	46	L	L	H	M	AND	ML
11	H	H	M	L	AND	M	47	M	M	H	L	AND	M
12	H	H	L	M	AND	M	48	M	L	H	L	AND	ML
13	H	H	L	L	AND	M	49	L	M	H	L	AND	ML
14	H	M	M	H	AND	MH	50	L	L	H	L	AND	L
15	H	M	L	H	AND	M	51	M	M	M	H	AND	M
16	H	L	M	H	AND	M	52	M	L	M	H	AND	M
17	H	L	L	H	AND	M	53	L	M	M	H	AND	M
18	H	M	H	M	AND	MH	54	L	L	M	H	AND	ML
19	H	M	H	L	AND	M	55	M	M	L	H	AND	M
20	H	L	H	M	AND	M	56	M	L	L	H	AND	ML

21	H	L	H	L	AND	M	57	L	M	L	H	AND	ML
22	M	M	H	H	AND	MH	58	L	L	L	H	AND	L
23	M	L	H	H	AND	M	59	M	M	M	M	AND	M
24	L	M	H	H	AND	M	60	M	M	M	L	AND	ML
25	L	L	H	H	AND	M	61	M	M	L	M	AND	ML
27	H	M	M	M	AND	M	62	M	M	L	L	AND	L
28	H	M	M	L	AND	M	63	M	L	M	M	AND	L
29	H	M	L	M	AND	M	64	M	L	M	L	AND	L
30	H	M	L	L	AND	ML	65	M	L	L	M	AND	L
31	H	L	M	M	AND	M	66	M	L	L	L	AND	L
32	H	L	M	L	AND	ML	67	L	M	M	M	AND	ML
33	H	L	L	M	AND	ML	68	L	M	M	L	AND	L
34	H	L	L	L	AND	L	69	L	M	L	M	AND	L
35	M	H	M	M	AND	M	70	L	M	L	L	AND	L
36	M	H	M	L	AND	M	71	L	L	L	L	AND	VL

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