Autonomous Real-Time Site Selection for Venus and Titan Landing using Evolutionary Fuzzy Cognitive Maps

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Abstract - *Future science-driven landing missions, conceived to collect in-situ data on regions of planetary bodies that have the highest potential to yield important scientific discoveries, will require a higher degree of autonomy. The latter includes the ability of the spacecraft to autonomously select the landing site using real-time data acquired during the descent phase. This paper presents the development of an Evolutionary Fuzzy Cognitive Map (E-FCM) model that implements an artificial intelligence system capable of selecting a landing site with the highest potential for scientific discoveries constrained by the requirement of soft landing on a region with safe terrain. The proposed E-FCM evolves its internal states and interconnections as function of the external data collected during the descent, therefore improving the decision process as more accurate information is available. The E-FCM is constructed using knowledge accumulated by experts and it is tested on scenarios that simulate the decision-making process during the descent toward the Hyndla Regio on Venus. The E-FCM is shown to quickly reach conclusions that are consistent with what a planetary expert would decide if the scientist were presented, in real-time, with the same available information. The proposed methodology is fast and efficient and may be suitable for on-board spacecraft implementation and real-time decision-making during the course of any robotic exploration of the Solar System.*

Keywords: Planetary Exploration, Planetary Landing, Autonomous Systems, Fuzzy Cognitive Maps

1 Introduction

Future unconstrained and science-driven NASA and ESA missions to explore planetary bodies in the Solar System will require soft landing in sites that have the potential to yield the highest geological and exobiological information. During the planning of any landing mission, scientists and engineers select an appropriate landing site on the planetary body of interest using data acquired during the reconnaissance of previously deployed robotic spacecrafts. The completeness of currently available information varies widely from body to body and depends critically on the number of missions deployed on the particular planet and/or natural satellite as well as on their geophysical properties (e.g. dense, thin or no atmosphere) which may inherently make the acquisition of surface data from orbiting spacecraft very difficult. For example, instruments on board spacecrafts currently orbiting Mars (e.g. Mars Reconnaissance Orbiter [1], Mars Odyssey [2]) are streaming a wealth of data about the red planet, thus providing a large amount of information to the scientists that can employ the available data to make the best possible landing site selection. On the contrary, other planetary bodies of high interest such as Venus and Titan have less available information and subsequently, a-priori landing site selection becomes more problematic. Due to a dense and opaque atmosphere which limits the electromagnetic bands available to passive optical instruments, both Venus and Titan have been mainly mapped using Synthetic Aperture Radar (SAR, e.g. Magellan SAR and Cassini SAR [3]) which generates images using the backscattered signal collected by the spacecraft antenna. SAR images have limited spatial resolution and they are harder to interpret, therefore making the ground-based landing selection process extremely difficult. Importantly, even in the case of Mars, a-priori selection of a suitable landing site is a complex process which involves the planetary science community at large. For example, NASA Jet Propulsion Laboratory has been organizing a series of workshops to actively engage Mars scientists to reach a consensus for the selection of the upcoming Mars Science Laboratory (MSL) landing site [4].

Whereas ground-based pre-planning and landing site selection is an important activity for any space mission comprising a lander, the final and best landing site selection may be possibly executed in real-time during the Entry, Descent and Landing (EDL) phase. Here, we define "best" as the landing site that has the potential to yield the highest potential for scientific discoveries and that satisfies specific landing safety constraints. Real-time, autonomous selection of such a site requires that the robotic lander is equipped with a system capable of a higher degree of autonomy. Such a system should (1) include software packages that enable fully automated and comprehensive identification, characterization, and quantification of features information within an operational region with subsequent target prioritization and selection for close-up reexamination (e.g. Automated Global Feature Analyzer, AGFA [5]); and (2) integrate existing information with acquired, "in transit" spatial and temporal sensor data to automatically perform intelligent planetary landing, which includes identification of sites with the highest

potential to yield significant geological and astrobiological information ([6],[7]) .

In this work, we design and simulate an advanced intelligent system capable of autonomously selecting landing sites using data coming in real-time from the lander sensors. We use Evolutionary Fuzzy Cognitive Maps (E-FCM, [8]) to model the cognitive reasoning of a planetary scientist that is presented with the same information available to the lander on-board computer and decides in real-time where to drive the spacecraft for safe landing. While a large numbers of techniques in the AI domain are available (e.g. fuzzy experts [9],[7]) , the E-FCM for real-time landing decision making was selected because of its ability to model complex processes comprising a large number of interacting parameters. Importantly, available experience and knowledge accumulated by planetary scientists can be easily translated in a cognitive map that is expressed through the use of concepts connected via causal relationships. Moreover, the ability of the proposed algorithm to reach conclusions in a fast and efficient way, make it ideal for real-time implementation on the spacecraft on-board microprocessor.

To our knowledge, FCMs have been only recently employed to design algorithms for autonomous interpretation of planetary data (see [10]). The main goal of this work is to show how FCMs in general, and E-FCMs in particular, can be used to advance the state of the art of autonomy in planetary exploration by providing an effective inference platform that can be easily understood by planetary scientists.

2 Autonomous Landing on Planetary Bodies

2.1 Landing on Venus and Titan: the Need for Autonomous Systems

Landing on planetary bodies with dense atmosphere such as Titan and Venus is extremely challenging. In any future science-driven and unconstrained landing scenarios, including soft precision landing (< 100 m) and pin-point landing (<1 m), autonomy will play more and more a critical role to a) provide autonomous selection of the landing site based on real-time data, b) implement a targeting program that will generate a flyable trajectory to the selected target and c) execute real-time guidance algorithms to drive the system to the desired location. Current flight-ready technology has been effective to land a spacecraft on a preselected region within a landing ellipse of 120x20 km (e.g. Phoenix Mission to Mars [11]). Future missions (e.g. MSL, [12]) have the potential to shrink the landing ellipse to less than 10 km. Clearly, autonomous, real-time landing site selection has never been implemented. The latter is extremely desirable because the selection takes place in real-time by reasoning on data collected during the descent to determine sites with the highest potential of scientific discoveries and avoid areas with high hazard potential.

In human history, only one landing probe has been delivered to the Titan surface, i.e. the Huygens probe, which landed on the Titan surface on January 14, 2005 [13]. The descent was completely preplanned and unguided due to scarce surface information. The probe landed on what is now interpreted to be a methane-rich outflow channel. During the descent, the camera system collected a set of images showing a plethora of interesting geological features which may have constituted interesting landing sites. Landing on Venus has been attempted many times as documented by the results from Venera and Vega missions [14]. Venus surface has been mapped using the Magellan SAR which is the only mean to probe the surface beyond its dense atmosphere. Figure 1 shows the landing ellipse of the region selected by Venera 10, which is also the region selected to test our design (see section 4). The region presents 8 stratigraphic units ([15]) and, for our analysis, has been subdivided in three regions. Region #1 is mainly comprised of what is classified as "Tesserae Units", i.e. ancient terrains comprising dislocated units of tectonic origin. Region #2 is mainly comprised of highly fractured plains that exhibit lobate flow field features. Region #3 exhibits a smooth (radar-dark) behavior interpreted as volcanic planes comprising materials that resembles to terrestrial volcanic rocks ([16]). In all Venera and Vega missions, the landing site has been preselected as well.

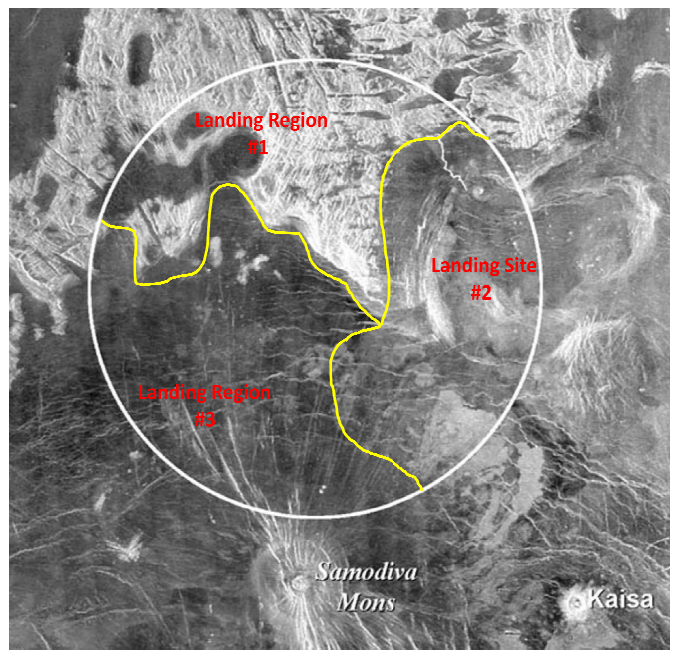

Figure 1: Venera 10 Landing ellipse. The area has been divided in three regions with features (real and hypothesized) that are used to test the E-FCM algorithm

2.2 Landing on Venus and Titan: The need for Autonomous Systems

Evolutionary Fuzzy Cognitive Maps (E-FCM, [8],[17]) may be considered as an extension of FCMs specifically developed to model variable internal states as well as the dynamic,

complex and causally related context variables (i.e. coming from data acquired during the landing descent). In its basic formulation, FCMs are digraphs designed to capture the cause/effect relationships exhibited by a system ([18]). Two basic elements form the backbone of the maps, i.e. nodes and arcs. Nodes are the concepts representing factors and attributes of the modeled system, e.g. inputs, outputs, states, variables, events, goals, as well as trends. Arcs are introduced to describe the causal relationships between concepts with a degree of causality. Extending this approach further, in E-FCMs, the concept states evolve in real-time as function of the internal mental state, external inputs and possibly external causalities.

Table 1: Concepts Description and Concepts Values

Concepts	Concept Description	Value
C1, C12, C23: Landing Region #1,#2,#3	Index for Landing Site Selection	Continuous Value [0,1]
C2, C13, C24: Potential for Scientific Discoveries (PSD 1,2,3)	This concept indicates the potential exhibited by the region to yield significant discoveries	Five fuzzy values, {VL,L,M,H,VH}
C3, C14, C25: Potential for Hazards (PHZ 1,2,3)	This concept indicates the regional potential for landing hazards	Five fuzzy values, {VL,L,M,H,VH}
C4, C15, C26: Volcanic Plain Features (VPF 1,2,3)	VPF indicates the level of presence for features associated to volcanic landforms	Six fuzzy values, {A,VL,L,M,H,VH}
C5, C16, C27: Flow-Like Features (FLF 1,2,3)	FLF indicates the level of presence for features volcanic flows	Six fuzzy values, {A,VL,L,M,H,VH}
C6, C17, C28: Ancient Terrain Features (ATF 1,2,3)	ATF indicates the level of presence for features associated with ancient terrains	Six fuzzy values, {A,VL,L,M,H,VH}
C7, C18, C29: Smooth Terrain (ST 1,2,3)	ST indicates the level of smoothness of the region	Five fuzzy values, {VL,L,M,H,VH}
C8, C19, C30: Rough Terrain (RT 1,2,3)	RT indicates the level of roughness of the region	Five fuzzy values, {VL,L,M,H,VH}
C9, C20, C31: High Slope Terrain (HST 1,2,3)	HST indicates the high slope level of the region	Five fuzzy values, {VL,L,M,H,VH}
C10, C21, C32: Low Slope Terrain (LST 1,2,3)	LST indicates the level of low slope level of the region	Five fuzzy values, {VL,L,M,H,VH}
C11, C22, C33: Featureless Terrain (FT 1,2,3)	FT indicates the level of featureless terrain of the region	Six fuzzy values, {A,VL,L,M,H,VH}

Indeed, each concept is equipped with its own update schedule as well as subjected to a small self-mutation probability. Moreover, the causal connection between concepts is fired according to a specified conditional probability. The evolutionary extension to FCMs has been chosen due to the nature of the landing selection process. During the Entry, Descent and Landing (EDL) phase, data are continuously streamed in real-time to the spacecraft computer and they are processed to determine the landing site using all available information. However, such data are remotely collected and subjected to uncertainty due to the limited resolution of the instrumentation. With the assumption that as the lander gets closer to the targeted region, more accurate information is available, the E-FCM must have the ability to adapt and dynamically update the connections strength to account for newly available data. In this case, differently than conventional FCMs, concepts are represented by tuples of properties, i.e. $\mathbf{A} = [\mathbf{A}_V, \mathbf{T}, \mathbf{PS}]$. Here, $\mathbf{A}_V$ denotes the fuzzy values of the concepts **C** (same as FCM). Concepts values generally range between [-1, 1] or [0,1]. For a system of N concepts, $\mathbf{A}_V = [A_{V1}, A_{V2},\ldots,A_{VN}]$ is an evolving vector that represents the time evolution of the each individual concept value C_i. $\mathbf{T} = [T_1,T_2,\ldots.T_N]$ is a Nx1 vector that represents the evolving time schedule of each concept. The latter accounts for the fact that various concepts may have a different real-time update schedule. $\mathbf{P}_S = [P_{S1},P_{S2},\ldots,P_{SN}]$ is the state mutation vector which account for the possibility that each concept may randomly alter its internal state in real time. According to Cai et. al. ([8]), the self-mutation probability must be modeled as small value to avoid system's instability.

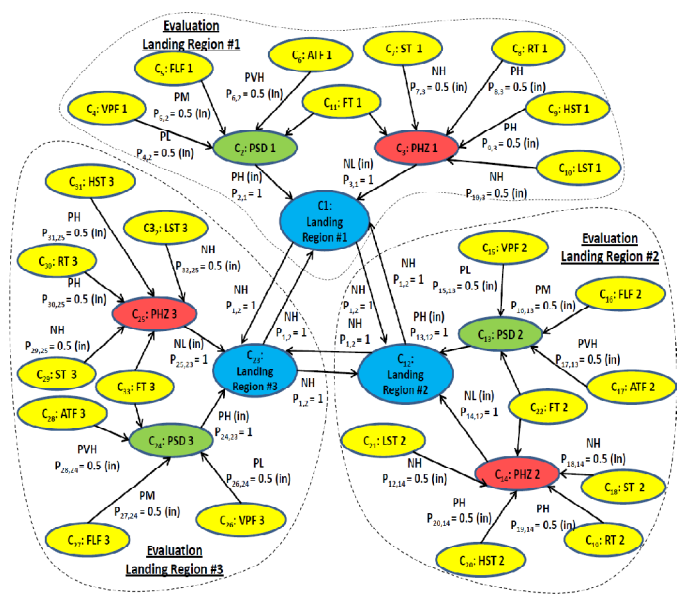

Figure 2: E-FCM topological structure. The weights are defined using fuzzy linguistic values (VL = 0.1, L = 0.25, M = 0.5, H = 0.75, VH = 0.9). P and N indicate respectively direct and inverse connection. Initial values of probabilities are indicated as well.

The causal relationship between concepts is defined as the tuple $\mathbf{R} = [\mathbf{W}, \mathbf{Pm}]$ which extend the conventional FCM approach (which uses only the fuzzy connection matrix) to allow the incorporation of uncertainty via fuzziness and randomness. For a system of N concepts, $\mathbf{W} = \{w_{ij}\}$ is the NxN weight matrix that represents the causal relationship between two concepts in fuzzy terms (e.g. high, low, medium, absent, etc.). The connection can be either positive or negative. $\mathbf{P}_m = \{p_{i,j}\}$ is the NxN matrix of causal probabilities between the interconnections. Causal probabilities may also be described in fuzzy terms. They represent the uncertainty of connections between concepts. For example, $p_{i,j}$ represent the probability that the concept A_i influences A_j with the strength

defined by the correspondent w_{ij}. The value A_i of the concept C_i is computed by accounting for all possible influences deriving from interconnected concepts as well as the causal probabilities deriving from $\mathbf{P}_m$. At each time interval and according to the predefined time schedule **T**, the concepts are updated using the following formula:

$$\boldsymbol{A}_i(k+1) = f\left(\boldsymbol{A}_i(k) + \sum_{\substack{i=1,N \\ i \neq j}} \boldsymbol{A}_j(k) W_{ji}\right) \qquad (1)$$

Here, f(·) is the activation function used to regulate the state variable (bivalent, trivalent or logistic). The weight matrix is evaluated according to the causal probability matrix and the value is randomly changed according to the self-mutating probability.

The development and construction of the E-FCM is executed using knowledge accumulated by field experts who define the type and numbers of concepts, the strength of the connections and also the causal probability matrix. Various methodologies are available to define the connections strength. Papageorgiu et. al. ([19]) proposed to define the strength of the connection between concepts using fuzzy IF-THEN rules in the following fashion:

IF value of concept C_i is B THEN value of concept C_j is C and the linguistic weight w_{ij} is E

Here, B,C,E are linguistic fuzzy values determined via appropriate membership functions with values in the range [0,1] for direct connection and [-1,0] for inverse connection. Indeed, for any of the established concepts, the experts determine the negative or positive effect of one concept on the others with a fuzzy degree of causation. As shown by [19], experts' opinions can be accounted individually via independent linguistic rules that are subsequently aggregated and de-fuzzified. Our group agreed on the structure of the map so that only one linguistic rule is defined to infer the fuzzy causal connection between concepts (i.e. fuzzy aggregation is not required).

3 E-FCM Methodology for Landing Decisions Making: the case of Venus

The problem of autonomous selection of a landing region that integrates published knowledge and real-time acquired information on the journey toward the planetary surface is a complex process that requires interaction between large numbers of parameters. Moreover, for a given scenario, defining the criteria that allow a clear definition of what is the region that yields the maximum possible scientific information is a matter of debate within the planetary science community. Here, we consider the case of landing on Venus and we focus on designing an E-FCM that selects the landing region, among the observables, that exhibits the terrain with the most ancient features and hence has the potential of unfolding a large portion of the geologic history of the planet ([17]). However, potential for scientific discoveries and geological understanding of any of the considered regions must be consistent with the ability of the spacecraft to safely land on the selected site. Because of the limited SAR resolution and the difficulty for its correct image interpretation, a-priori analysis of potential Venusian landing regions may not unfold critical features that may yield higher (or lower) potential for scientific discoveries and/or potential hazards. Thus, the overall goal is to construct an E-FCM that ingests data during portions of the EDL and, for the pre-selected regions, it infers what is the potential for scientific discoveries (in the sense clarified above) and potential for hazards. Such indicators are then used by the map to autonomously select the best site for a safe soft landing. The proposed E-FCM evolves in time according to a prescribed schedule to a) account for data streamed into the system from the sensors and b) adapt for reasoning under uncertainty and ambiguity of the data available as function of time. Our team designed an E-FCM model that accounts for 33 interconnected concepts (see table 1). The selected concepts, which have been linked to data that may be determined using real-time feature extraction software (e.g. AGFA, [5]) are divided in three major groups. Each group contains input concepts that have been selected to account for features that are required to infer both the potential for scientific discoveries and the potential for hazards for any of the three regions located within the selected landing area on the southern part of the Venusian Hyndla Regio (Figure 1). Indeed, the E-FCM is asked to select one landing site among the three pre-identified landing regions using hypothesized data acquired during a portion of the descent flight. For each of the three regions, a group of 4 variables are identified to influence the potential for scientific discoveries (e.g. C_4, C_5, C_6, C_{11} for landing region #1) whereas a group of 5 variables are shown to influence the potential for hazards (e.g. C_7, C_8, C_9, C_{10}, C_{11} for landing region #1). Both potential for scientific discoveries and potential for hazards influence the landing site selection. The weight matrix is selected by our team's planetary experts. For example, the link between concept C_6 (Ancient Terrain Features for Landing Site #1) and C_2 (Potential for Scientific Discoveries on Landing Site #1) is established to be "Positive Very High (NVH)" or using an IF-THEN formalism:

IF a small change in the value of concept C_6 occurs THEN a very high change in the value of the concept C_2 is caused. <u>Inference:</u> the influence of C_6 on C_2 is Positive Very High.

Conversely, the influence between the value of the concept C_7 (Smooth Terrain in landing Site #1) and C_3 (Potential for Hazards on Landing Site #1) is "Negative High (NH)" or:

IF a small change in the value of concept C_7 occurs THEN a negative high change in the value of the concept C_3 is caused. <u>Inference:</u> the influence of C_7 on C_3 is Negative Very High.

In absolute terms, the influence of the potential for scientific discoveries and hazards on the landing region concepts has a

value of PH and NH, respectively. However, the connection is selected to be time dependent in the following sense: During the descent toward the targeted area, the influence of the potential for scientific discovery is initially set to be PH and the potential for hazard is initially set to be Negative Low (NL). As the lander gets closer to the surface, the influence of the hazard on the landing site selection is increased (limit to NH when the final decision is made) whereas the influence of the potential for scientific discoveries is reduced (limit to PL when the final decision is taken).

Table 2: Ground Truth for the Landing Scenario #1

Scenario # 1	**Landing Region #1**	**Landing Region #2**	**Landing Region #3**
VPF	L	L	VH
FLF	L	VH	L
ATF	H	A	A
ST	H	H	H
RT	L	L	L
HST	L	L	L
LST	H	H	H
FT	VL	VL	VL

Table 3: Ground Truth for the Landing Scenario #2

Scenario #2	**Landing Region #1**	**Landing Region #2**	**Landing Region #3**
VPF	L	L	VH
FLF	L	VH	L
ATF	H	A	A
ST	L	H	H
RT	H	L	L
HST	H	L	L
LST	L	H	H
FT	VL	VL	VL

The goal is to ensure that priority is given to landing safety especially when less uncertain, higher resolution data are available. The probability matrix is also established by our field experts and, for certain connections, it is assumed to be time-dependent. As a general guide, the probability of connection between input data (e.g. concepts C_4-C_{11}) and derived concepts (e.g. C_2, C_3) is assumed to increase with the time of flight to account for the fact that uncertainty in data is less pronounced and therefore the connection is more probable. Figure 2 illustrates the designed E-FCM model for landing site selection with numerical values for weights and causal probability. Importantly, the map topology has been selected such that the there is an internal competition to select the winning landing site.

4 Simulations and Results

After the construction of the E-FCM, a number of scenarios have been considered to simulate the behavior of the algorithm. It is assumed that the scientific team responsible for soft landing on Venus, selects the southern part of Hyndla Regio as landing area (see figure 1). The area is subdivided in three landing sites for which the "ground truth" is assumed to be known and established a-priori. The EDL trajectory has been designed such that the lander can autonomously select the landing site using the E-FCM before t_F, time after which guidance constraints impose that the other two regions are outside the reachability domain. It is also assumed that the spacecraft is able to collect data for 120 seconds before t_F is achieved.

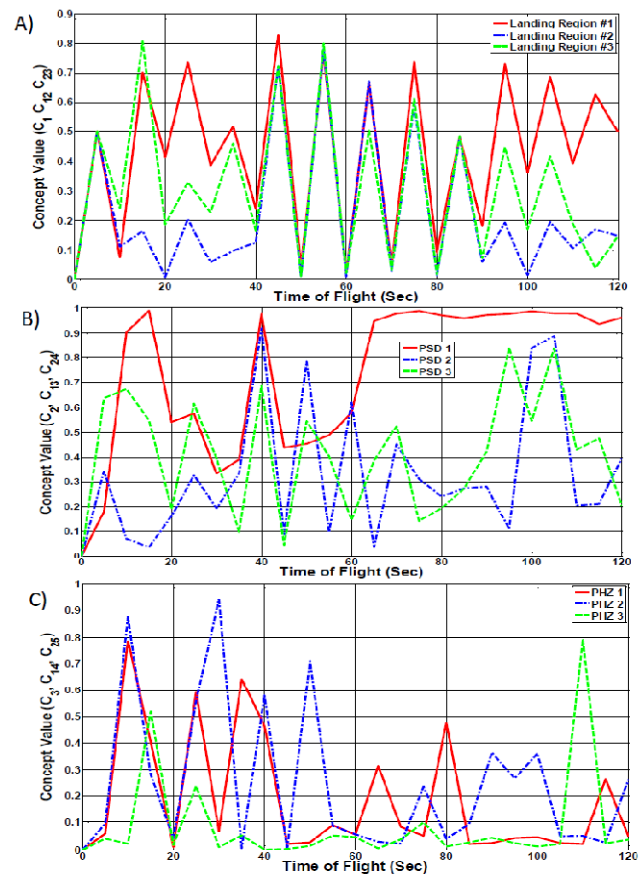

Figure 3: Landing scenario #1 E-FCM time-dependent output for selected concepts. A) Landing selections values; B) PSD values; C) PHZ values.

The information is updated each 5 seconds during which the lander acquires and processes images to extract the features that are input to the E-FCM. For any of the established scenarios, it is assumed that the spacecraft collects data with an uncertainty that is function of the flight time. More specifically, the "ground truth" is set to be the mean value of a data sampling Gaussian distribution with a standard deviation that decrease as t_F is approached (i.e. as the lander

gets closer to the surface, the improved instrument resolution yields more accurate data). With this setting, data are continuously updated and the E-FCM run to infer, at each given time interval, what is the best landing region. Finally, it is noted that all concepts are updated synchronously (same time schedule) and no self-mutation probability is implemented. The following two scenarios are considered.

Scenario #1: For the first scenario, the "ground truth" is constructed using fuzzy linguistic values as reported in table 2. In this case, the available hypothesized data show a region #1 that is the most attractive for landing. Indeed, the large presence of ancient terrain features makes the region more attractive from the prospective of unfolding the ancient geological history of Venus. All regions are shown to be very safe safe for landing (plenty of smooth and low slopes terrains). Landing regions #2 and #3 have also flow-like features and volcanic terrains which may be of scientific interest but lower priority. It is therefore expected that the E-FCM selects Landing Region #1 as landing scenario. The simulation is initiated by setting up an initial concept value vector whose input values are assigned using a normal (Gaussian) distribution. The E-FCM evolves both weights and concepts values with input values updated each five seconds. The simulation results are reported in figure 3 which shows the time evolution of landing values as well as PSD and PHZ for all regions. As evident from figure 3A, the highest value is reached by region #1 which wins the competition with the other two regions. As the acquired data increasingly indicate that all regions are safe for landing, the E-FCM chooses the region with the highest potential for scientific discoveries, consistently with our expert analysis based on ground truth data.

Scenario #2: The second scenario is similar to the first one. As reported in the ground truth table (see table 3), landing region #2 and #3 are identical to the first scenario. Landing region #1 still shows a high presence of ancient terrains which makes it attractive from a scientific discovery point of view. However, the region now indicates a very robust presence of rough terrain and high slope surface which is a strong indication of potential for hazards which should discourage the landing selection. Figure 4 shows that the E-FCM reached the conclusion that region #1 has both highest PSD and PHZ and subsequently disregard it for landing selecting landing region #2 which ahs lowest scientific interest but exhibits safer landing terrains.

5 Conclusions

The artificial intelligence approach used in this work focuses on developing evolutionary fuzzy cognitive techniques that mimics the planetary scientist selection process for landing site selection, with special emphasis on Venus and Titan. It is shown that the proposed E-FCM reaches the same conclusions as field experts and it is fast enough to be suitable for real-time, on-board implementation. The outlined methodology has the potential to be the premiere AI choice for cognitive reasoning on data for planetary exploration.

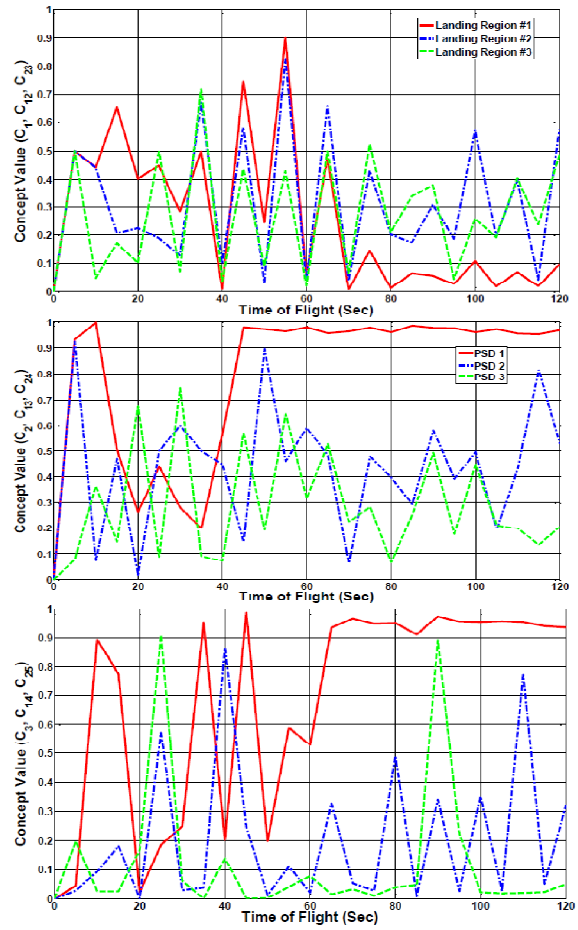

Figure 4: Landing scenario #2 E-FCM time-dependent output for selected concepts. Top: Landing selections values; Middle: PSD values; Bottom: PHZ values.

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