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Toward Neuromorphic Odor Tracking: Perspectives for space exploration

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Abstract.

Autonomy is an essential factor to maximize the scientific return of exploratory missions, and it increasingly motivates the development of intelligent technologies that reduce the need for remote control or human supervision. This is the case for instance in the fields of rover navigation or on-board science analysis for planetary exploration. Interestingly, some of the tasks involved in such endeavors are also faced and efficiently solved by biological systems in nature, e.g. the animal olfactory system is able to autonomously detect and track cues (molecules) over long distances; it can robustly cope with sparse or noisy data, and it requires low computational complexity and energy consumption. On account of such capabilities, technologies that find inspiration in the neural architecture of biological systems present intrinsic advantages that give answers to the requirements of space environments. This paper outlines recent work in the fields of bio-inspired autonomous navigation and neuromorphic chemical sensing. We envision that these two approaches can be merged to produce novel techniques for autonomous exploration in space applications.

1 Introduction

For decades space exploration has been involved with searching for traces of past or present life and water on other planets along with measuring geophysical parameters relevant to planetary evolution. Examples of upcoming exploratory missions sharing these goals include the 'ExoMars' mission led by ESA, which will perform measurments of the Martian soil and rocks, collecting and analyzing particles by means of a surface Rover [39]. Likewise, the NASA 'ARES' Mission will study the atmospheric composition of the red planet using an Unmanned Air Vehicle (UAV) that will be flown through the near-surface atmosphere while collecting samples of its chemistry and dynamics [34].

Common to all aforementioned tasks is required to detect and track chemical components in an unknown environment. This involves several challenges. First, relevant particles or blends are to be detected and discriminated on-line. Precise gas sensor technologies and on-board analysis are required to classify relevant molecules in real time, thereby coping with their short-time scale, high dimensionality and quickly changing amplitude [15]. Traditional pattern recognition models based on attractor states may prove too slow for such purposes.

Secondly, exploration needs to be driven toward ar-

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eas of high scientific impact. Navigation must be autonomous and efficient, able to deal with data that is sparse, noisy and subject to turbulence. Note, that in real environments, patches of high concentration are constantly surrounded by wide voids where no relevant information is available. This makes navigation a complicated task for which simple approaches (e.g., gradient-based) fail, since gradients constantly fluctuate in magnitude and direction, and do not point toward the source [35].

When considering space applications, additional constraints must be accounted for, namely, limited energy consumption and physical space. Computational complexity must thus be kept to a minimum.

Interestingly, olfactory source localization is a common task in nature, and many animals constantly solve it to locate food or find mates with high accuracy and limited resources [26]. Moth and Bacteria are among the most illustrative and better documented examples of scent tracking. The former use their antennae to detect pheromones released by females, and employ them to track the plume toward their mate [2]. Bacteria on the other hand rely on local searches to move toward a source of nutrients [3]. To this date, neither the discrimination capabilities achieved by biological systems, nor their efficiency in exploration, have been replicated by artificial counterparts.

Several biomimetic solutions have attempted to draw inspiration from nature, and to apply them to robotics as an alternative to classic engineering approaches [14, 30]. Of particular interest, neuromorphic technologies mimic the *architectural structures* present in the nervous system. They are usually implemented in analogue circuits that consume little power and they exploit parallel computation which allows real-time performances. Such concepts provide an ideal technical framework to deal with the requirements of space applications. Recent successful applications include neuromorphic vision-based spacecraft landing, derived from insect optic flow strategies, and integrated within Very Large Scale Integration (VLSI) sensors [27, 22].

In this paper, we report advances in both neuromorphic chemical detection and autonomous navigation. We further outline how, when combined, such techniques may prove valuable in the framework of planetary exploration.

2 Robot navigation

2.1 Toward full autonomy

Intelligent decision-making in space unmanned vehicles is essential to overcome the limitations caused by communication delays and overloaded bandwidths. It allows the exploration of distant planets without direct human supervision, and thereby to replace impractical remote control [1].

To this day, however, autonomous navigation has been mostly limited to providing basic behaviours, e.g. obstacle-avoidance or detection of traversable areas. Higher-level behaviours that require scientific expertise and long-term plans (as is the case when seeking chemicals) are still human controlled. Additional autonomy has recently been deployed using planning and scheduling techniques [38, 10, 6] in order to flexibly *redirect* exploratory paths on-line, and thereby to account for new features of interest discovered along the way. Yet this is only local and with limited range of action within the pre-established long-term plan outlined from Earth. Fully automating exploratory operations would require that the whole navigation toward promising areas be decided onboard by the agent itself, guided by interactions with its environment and motivated by an intrinsic interest in the final goal.

Completely autonomous source localization has been attempted on Earth through a variety of techniques, either purely probabilistic or inspired from biological systems. The former uses intelligent sensing and planning to reason about the world, but it often suffers from the sparseness of information far from the source, and it proves to be truly efficient in dense conditions only, i.e. close to the source where the plume can be considered as a continuous cloud [28]. Bio-inspired approaches, on the other hand, can yield impressive results even far form the source [17, 14, 29], but often address the problem only from a *behavior imitation* perspective, i.e. they mimic the choices performed by animals through a rule-based approach, regardless of the mechanism from which the behavior emerges. This raises the question of how well such strategies may be adapted to new scenarios (if at all) or even be optimized when considering added constraints such as those imposed by space. A proper adaptation would instead require tuning and rewiring the underlying neural architecture.

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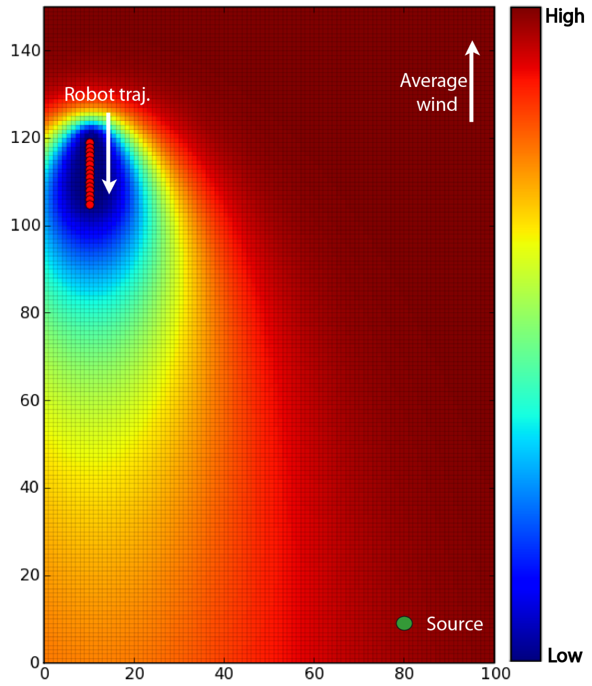

Figure 1. *Infotaxis. Example of belief (probability map) for the location of the source after 10 steps (red dots). No 'cues' are detected in that time. Locations in front of the agent become less probable as the agent navigates forward without encounters, thereby increasing the likelihood of locations on the sides. The shape of the belief (Gaussian-like) is inferred from the physics description of how cues spread in the environment when transported by the wind.*

2.2 Infotactic strategies

Infotaxis [40] conveys the advantages of both approaches previously mentioned. It is based on Reinforcement Learning (RL) approaches, and fully exploits the capabilities of autonomous on-line learning. The agent discovers the direction leading to the source by iterative interactions with its environment, driven by a decision-making strategy that efficiently combines exploratory patterns with information exploitation.

Interestingly, although animal patterns are not preprogrammed or imposed through explicit rules of movement, behaviors such as casting or zigzagging (extensively documented in moths) do actually emerge naturally from the underlying architectural model [20]. This represents a promising baseline from which to derive extended strategies, adapted to other scenarios. As a matter of fact, even though initially restrained to the problem of scent tracking, infotaxis actually embodies a *general* framework for intelligent navigation and source localisation with sparse cues. Its core components are outlined hereafter.

Algorithmic foundations.

Infotaxis is built around two core components: Uncertainty modeling and decision-making. The former is achieved through an internal description of the world (physical description of how cues spread in turbulent environments when transported away from the source), which can be used to interpret encounters and thereby to infer the likelihood for the source to be at a given location.

In the scenario considered in [40] (odor cues spread in an open environment), the internal model corresponds to the spatio-temporal profile of odor plumes (as derived from the equations of diffusion-advection). Since molecule dispersal is subject to high degrees of turbulence and randomness, a detailed description of the environmental dynamics is unfeasible; instead, a time-average distribution of the detection-rate R is calculated, to which a random component is added, i.e. actual encounters are sampled independently from a poisson-distributed variable.

Based on this physical model, a *probabilistic belief* is built (Fig. 1) given the trace of past perceptions (in a similar way to [28]). Note that both encounters and non-encounters provide information and are used to iteratively update the belief, which is then relied upon for the decision-making. The strategy attempts to maximize the expected amount of 'knowledge' acquired in the next step, as quantified in terms of the entropy of the aforementioned probabilistic map. Note that this differs from classical approaches in that the agent does not directly target the most likely location for the source, but rather the one where he expects to 'learn' more about its surrounding.

The (expected) uncertainty in future steps is derived from two terms: A first term which evaluates the *probability of finding the source*, and a second one which computes the *amount of knowledge* gathered even if the source is not found. The first term corresponds to the exploitative choice; the robot chooses to go in the direction that maximises its (expected) chances of finding the source (regardless of other considerations) whereas the second term represents the explorative decision which pushes the robot to go to regions where it might detect

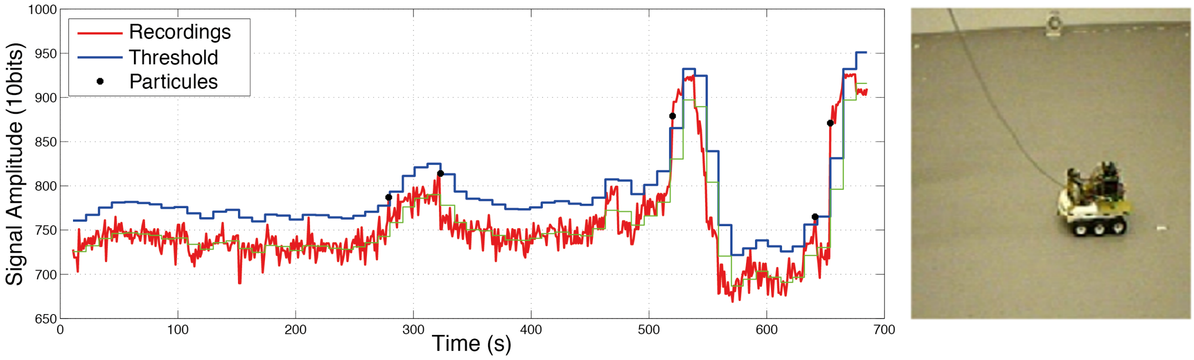

Figure 2. ***Left.*** *Real recordings (red) with a heat sensor at sampling frequency* f *=10Hz, and derived 'cues' (black dots) to be employed by infotaxis when guiding the search. A moving window (blue) is used to filter the signal while preventing consecutive correlated hits from being overcounted, thereby ensuring that 'cues' are appropriately derived from the sensor measurements* ***Right.*** *Experimental setup, koala robot endowed with the sensor, and heat source.*

new cues (regardless of whether the source is actually believed to be in that direction or not). This balance is essential for the strategy to be effective and provides the model with a robustness that makes it especially suitable for turbulent environments. Its efficiency was shown indeed to outperform more classical approaches [40]. Note that the horizon considered when predicting rewards consists of a single step, but could easily be extended to account for elaborated planning.

2.3 Facing real environments

We addressed the problem of verifying that infotactic strategies may prove equally efficient under real experimental conditions. It is well known that matching the complexity of the world in computational models is highly challenging, and usually it is necessary to make simplifications or assumptions to help make the problem tractable. On the contrary, robotic agents are confronted with the real environment and hence provide a testbed to assert complete and rigorous results. It is also an essential step to ensure that algorithmic concepts can be implemented with the available technology and employed for real-world applications.

The key point at the core of infotaxis is the randomness of odor encounters. This randomness is explained by the turbulence of the medium (particles spread through diffusion-advection), and it motivates the use of an uncertainty-minimisation approach. Cues are modeled in simulation through stochastic mathematical descriptions, and it is assumed that they are independent and uncorrelated. Yet in reality an odor patch covers a certain volume and presents extended spatiotemporal characteristics. Even though inherently random, this structure will give rise to consecutive non-independent 'cues'. For infotaxis to be fully efficient, consecutive detections should not be overcounted. In [24], we calculated the posterior probability distribution from a modified model that accounts for correlated hits, and is built around *transitions* from no-detection to detection rather than on single hits. In our implementation, this is achieved by means of an adaptive filter, calculated over a moving time-window (Fig. 2).

Furthermore, electronic sensors must be chosen so that the requirements of the model (in terms of sensitivity and speed) are met. Because odor sensors usually require long degassing times and saturate easily, they are unable to respond to the requirements of infotaxis. We chose as an alternative to use heat sensors, which do not saturate easily and react at high speed. We note that the spatiotemporal distribution of heat is identical to that of odor, and thus no loss of accuracy is brought in by this adaptation. Alternative solutions for chemical sensing that draw inspiration from the animals neural information system are further outlined in section 3, along with their advantages.

Infotaxis robustness and effectiveness was then tested by means of a real robotic framework (Fig. 2 – right). Identical distributions were obtained, both for the search time required until finding the source, and for the number of encounters required (Fig. 3), thus ensuring that its main properties are preserved when applied in reality. Note also that the internal model relied upon

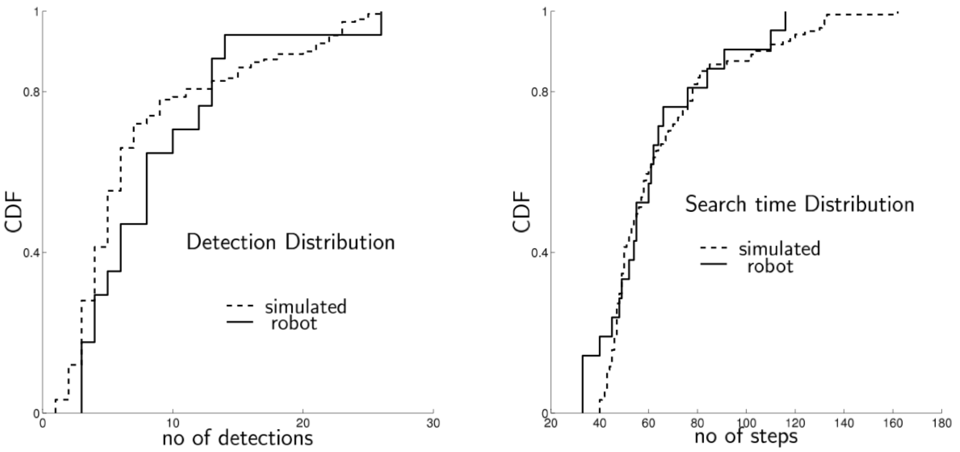

Figure 3. *Comparison of robotic and simulated results: cumulative distribution of the number of steps until finding the source (left) and of the number of cues required to reach the goal (left).*

by the agent requires parameters such as wind speed and direction. Which in reality may vary over time and differ from the estimated ones. The robustness of infotaxis was thus evaluated even with respect to *inaccurate* modeling by the agent; the parameters were not fine-tuned or adapted on-line, yet despite this discrepancy the robot was able to find the source within reasonable time limits.

The biomimetic characteristics of the navigation were also preserved in our robotic implementation. Robot trajectories were shown to exhibit animal-like patterns such as ‘extended cross-wind’ or ‘zigzag upwind’ [24]. The track angle histogram also maintains a distribution similar to that observed in moths.

3 Artificial olfaction

Molecule sensing and discrimination is being deployed in a range of space projects. Examples of on-board analysis and recognition include the Mars Organic Molecule Analyzer (MOMA) embedded within the ExoMars rover, that will analyze gases in the Martian atmosphere, attempting to separate and identify specific components. Complementary approaches that help facilitate this task would prove highly useful.

In this regard, it has been suggested that the animal olfactory system exploits network dynamics to improve the recognition of different inputs. They make use of the transient response and decorrelate different inputs by *mapping* them into a higher dimensional space that exploits the number of possible spatio-temporal combinations [30]. Under this grounding premise, recognition models built out of a similar structure could prove extremely efficient for real applications. Neuromorphic engineering is therefore a promising tool for building odor classification systems.

This technology may also be implementable as part of gas sensor employed in every day-life problems (e.g., CMOS). Progress so far in this direction has been hindered by the high price of these devices, and considerable effort has been devoted to developing low-cost gas sensors using CMOS technology, and combining them with MEMS for instance. This has led to the implementation of low-power smart gas sensors. A recent review by Gardner et al. [12] summarizes the main latest achievements in the field of integrated CMOS gas sensors.

3.1 Neuromorphic computation for olfactory systems

Neuromorphic VLSI devices comprise hybrid analog/digital circuits that implement hardware models of biological systems, using computational principles analogous to the ones used by nervous systems [21].

During the last decade the neuromorphic engineering community has made substantial progress by developing the technology for constructing distributed multichip systems of sensors and neuronal processors that operate asynchronously and communicate using actionpotential-like signals (or spikes) [7, 23]. The main advantages of VLSI networks of spiking neurons permit the embodiment of this platforms on robotic devices, providing the circuits with realistic inputs which are affected by the interaction of the robot with the environment.

Recent advances in chemosensors [12], a better understanding of the signal processing principles of biological olfactory systems and progress in the technology for constructing distributed spiking multi-chip neuromorphic systems, have made it possible to consider implementing compact, low-power, biologically inspired neuromorphic olfactory systems.

These systems are often modular. The sensing (see [32] for a recent review), the signal processing (e.g., [31]) and the artificial neural network pattern recognition system (e.g., [9, 33]) are implemented separately using various technological means (sensors with different transducer principles, conventional software algorithms, general purpose digital computing devices and custom hybrid analog/digital VLSI devices).

Within the biologically inspired olfactory systems proposed in the literature the most representative example of a neuromorphic olfaction device was recently suggested by Koickal et al. [13]. They presented a fully integrated neuromorphic olfaction chip comprising a chemosensor array, a signal conditioning circuitry and a spiking neural architecture with on-chip spike time dependent plasticity [19].

We propose a modular neuromorphic approach for testing olfactory coding and signal processing hypothesis derived from the study of insects. The long term goals of this research include the development of novel algorithms for chemical sensor data classification based on principles extracted from biological olfactory systems.

The choice for modularity provides two main advantages in comparison to a fully integrated neuromorphic olfaction chip:

1. commercially available chemical sensor arrays can be easily integrated in the neuromorphic system.
2. possibility to test different network topologies by means of spiking multi-neuron Address Event Representation (AER) chips and the related hardware infrastructure[1].

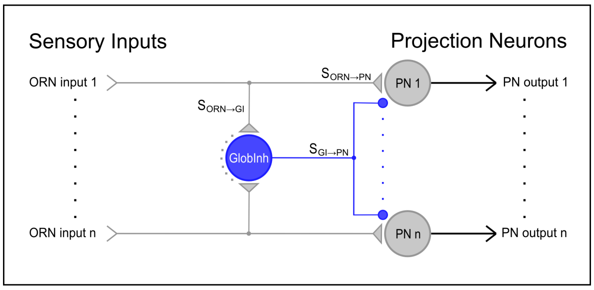

Figure 4. *Simplified model of the AL studied in [4]. Small triangles: excitatory connections. Small circles: inhibitory connections. Weights of excitatory and inhibitory connections (gray and blue pathways) are the only free parameters used to study the behavior of the network.*

The olfactory system of insects provides an ideal substrate for studying the information processing in biological neural networks for several reasons. Firstly, it is a 'small' system, i.e. the first olfactory relay in insects, the Antennal Lobe (AL), consists of a relatively small number (ca. 50 in *Drosophila*) of functionally distinct processing units or glomeruli. Secondly, it exhibits a stereotyped connectivity; the glomeruli are zones of high synaptic convergence between the axons of one type of Olfactory Receptor Neurons (ORN) and the dendrites of a few Projection Neuron (PN) projecting to higher brain areas [41]. Finally, the odor code is conserved between individuals which is helpful for the systematic comparison and pooling of experimental results.

In the insect glomeruli, inhibitory modulation of the AL activity is achieved by the interaction of Local Interneuron (LN) with ORN and PN. These intra-AL connections have a significant influence on the processing of information in the AL [42, 37]. The role of these inhibitory networks in shaping and processing olfactory information is not fully understood, despite a number of studies that have illustrated the importance of inhibition in the AL. In [4], we studied a network architecture with feed-forward global inhibition based on a previous study by Silbering and Galizia [36] (see Fig. 4) by using a linear model, a spiking software simulation and a neuromorphic implementation.

We used the linear model to provide a complete char-

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[1] In recent years we have witnessed the emergence of new asynchronous communication protocols that allow aVLSI neurons to transmit their activity across chips using pulse-frequency modulated signals (in the form of events, so-called spikes). One of the most common asynchronous communication protocols used in these types of systems is based on the AER [18]. Systems containing more than one AER chips can be assembled using off-chip arbitration and lookup tables to map address-events from one chip to another, implementing arbitrary network topologies. Infrastructures for constructing multi-chip pulse-based neuromorphic systems based on AER have been developed by several researchers (e.g., [5, 8, 25, 11, 7]).

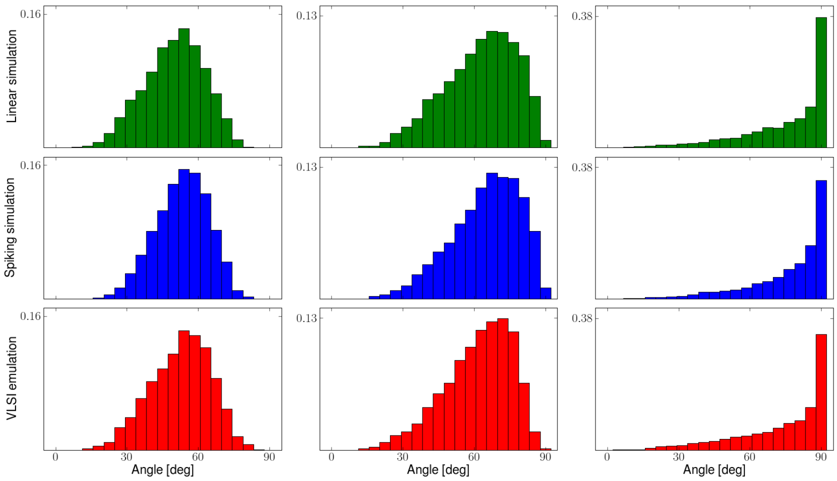

Figure 5. *Histogram of angles between activation vectors of odor pairs for the three simulations (rows) and for three values of inhibition strength (columns) presented in [4]. Increasing inhibition strength (from left to right) produces a shift of the angle distribution toward the* 90 *degrees limit, therefore increasing odor discriminability.*

acterization of the parameter space. The spiking simulation on the other hand provides the advantage of including the temporal dynamics in the model but has the drawback of being computationally intensive, especially for large network simulations. Alternatively, the neuromorphic VLSI emulation has the advantages of the spiking simulation in a compact, low-power, real-time system.

As shown in Fig. 5, we compared the behavior of the network in response to calcium concentrations measurements of odor responses in *Drosophila Melanogaster* for the three different simulation approaches.

One hypothesis about the role of the AL in the olfactory processing stream is to increase odor discriminability. In the AL, all axons with the same receptor expression profile converge onto a single glomerulus [41], so that the array of activity values of each ORN for a given odor represents a vector in a multidimensional space. Intuitively, we can consider the Euclidean angle between pairs of vectors as a measure of odors proximity, thus the network should increase angles to improve odor discriminability.

The table in Fig. 5 presented in [4] shows the distribution of angles (computed for all possible odor pairs) for the three simulations (rows) and for three values of inhibition strength (columns). When inhibition is disabled (left column) the PNs angle histogram is identical to the input (ORN) angle histogram for the linear simulation (top graph). When inhibition is enabled (center column) an average increase in angles between odors is observed in the three models. This network effect can be increased by increasing the strength of inhibition (right column).

These results showed that inhibition could be used by the AL to increase angles between odor pairs and therefore improve odor discriminability. The three models show comparable results.

Apart from studying the role of local inhibition in the AL, this work was very useful to establish a hardware framework for implementing models of olfactory computation. The neuromorphic neural network studied in [4] can be used as a preprocessing stage for an odor classifier. We are currently investigating a neuromorphic system for odor classification using the same data presented in [4], and comparing the classifier performance on the network's input and output data.

4 Perspectives for space

Infotactic navigation strategies have been tested so far in the case of olfaction only, i.e. for scent-tracking and odor-source localization. Nevertheless, the concept only requires certain features to work (cues encountered along the way as the agent navigates, providing information about where the source is more likely to be, along with a model of the environmental dynamics), and it hence represents a quite general approach that may be applicable to different scenarios with equal degrees of

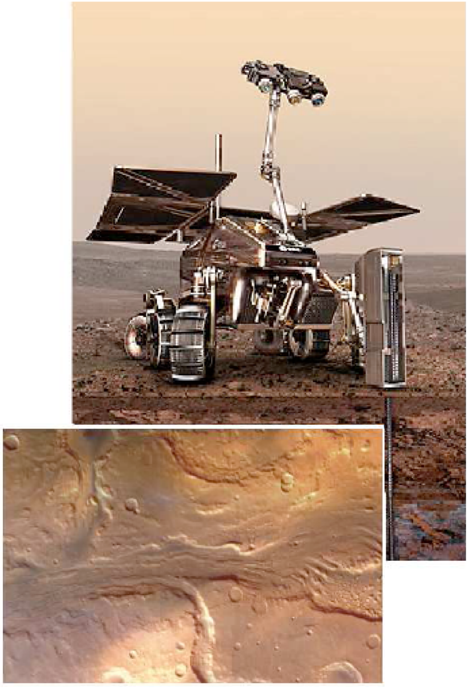

Figure 6. *Exomars rover [39] and riverbed along which fully autonomous water-source localisation may be considered.*

success.

Under such premise, it may be of interest to consider whether similar approaches could be used for space-related applications as the ones outlined in the introduction, for instance in the framework of finding footprints of biological activity. A key point is that the goal is treated as a source that spreads cues in the environment in a way that can be modeled, and relied upon when reasoning. Rover infotactic navigation would help guide the search toward areas of scientific interest (e.g., a crater, or the source of a dry river - Fig. 6).

These navigation strategies must be supported by on-board detection and real-time classification of chemical components. Integrated sensors and neuromorphic olfactory systems described above are ideal candidates for achieving these demanding tasks. The results presented in [4], summarized in section 3, provide a promising substrate for exploring hardware implementation of real-time chemical detection and classification devices. Furthermore, the neuromorphic technology can guarantee low-power consumption and compactness, essential for space applications. In particular, the hardware framework presented in [4] is relevant for robotic scent tracking in space exploration for the following reasons:

1. The neuromorphic chips used are massively parallel and operate in real time, regardless of the size of the implemented neural network.
2. The analog circuits modelling spiking neurons and dynamic synapse are operated in the transistor's subthreshold regime [16], therefore producing currents of the order of pico-Amperes and leading to very low power consumption.
3. Miniaturized systems can be implemented after a prototyping phase used to explore different architectures.
4. The spiking neural networks implemented in our neuromorphic chips can exploit temporal dynamic analogues to those observed in biology to achieve improved odor classification.

5 Conclusion

We have presented both software and hardware bio-inspired alternatives to classical robot navigation and odor-sensing processing. These exploit the structure of neural systems, their low energy consumption and small size, making them very well adapted to the requirements of space applications. Specifically we envision that implementing infotactic navigation supported by neuromorphic sensing and processing will lead to efficient and robust strategies that could allow full autonomy to be contemplated in exploratory rovers. These would intelligently guide the search for chemicals without human supervision.

In addition, alternative applications that go beyond mere odor recognition and tracking may also be considered. The presented models can be extended to account for additional constraints and scenarios, and may therefore be considered as a baseline from which to derive global searching strategies with sparse or noisy cues. Examples could include autonomous satellite guidance, or extensions that cope with limited measuring capabilities. Note that these may be included in the model as constraints, which might lead to substantial changes in the strategies adopted depending on the reward-to-cost ratio considered.

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